

**THE REPUBLIC OF TURKEY
BAHÇEŞEHİR UNIVERSITY**

**CREDIT RISK MODELING IN CORPORATE
AND INTERNATIONAL FINANCE & INTERNAL
RATING SYSTEM METHODOLOGY**

Master's Thesis

AHMET AKYILDIZ

İSTANBUL, 2010

**THE REPUBLIC OF TURKEY
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THE GRADUATE SCHOOL OF SOCIAL SCIENCES

CAPITAL MARKETS AND FINANCE

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AHMET AKYILDIZ

Thesis Supervisor: DOÇ.DR. HASAN EKEN

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Name/Last Name of the Student: Ahmet AKYILDIZ

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Prof.Dr.Selime SEZGİN
Director

I certify that this thesis meets all the requirements as a thesis for the degree of Master of Arts.

Prof. Dr. Ümit EROL
Program Coordinator

This is to certify that have read this thesis and that find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Arts.

Examining Comittee Members
Title Name and Surname

Signature

Doç.Dr.Hasan Eken

Prof. Dr. Ümit EROL

Dr.Hakkı Öztürk

ABSTRACT

CREDIT RISK MODELING IN CORPORATE AND INTERNATIONAL FINANCE & INTERNAL RATING SYSTEM METHODOLOGY

Akyıldız, Ahmet

Capital Markets and Finance

Thesis Supervisor: Doç.Dr.Hasan Eken

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The global financial crisis that started in September 2008 has thrown economies around the world into recession. To separate supply and demand effects, relate bank lending to a bank's willingness or ability to lend during the crisis. Focus on the role of deposits and revolving credit lines in mitigating and exacerbating the effects of the turmoil in financial markets and money markets. At the same time, investors will withdraw from money market funds that invest in commercial paper, and instead place their money in insured deposits so money cycles entered the chaos period.

On the one hand many people are concerned that those responsible for the financial problems are the ones being bailed out, while on the other hand, a global financial meltdown will affect the livelihoods of almost everyone in an increasingly inter-connected world.

So the entire world has lived the largest idle permanent damage with in lending process. The damage demonstrated a large-scale of banking activities. Wrong size risk management plans on paper did not exist in real terms activity, during this period financial giants plunged into debts day by day.

In this context, I tried to explain ; credit management and loan type, credit rating, credit risk management scoring and processes, parsing functions, linear regression models & process of lending, measurement techniques, exponential transformations in work, quantitative measurement of the model & character models, calibration, explaining that the Turkish banking system in the loan portfolio credit risk modeling, credit risk rating models and explained the effect of the components with all items.

Keywords: Loan pricing, risk management, credit risk, modeling, internal rating,

ÖZET

ULUSLARASI FİNANSDA VE ŞİRKETLERDE KREDİ RİSK MODELLEMELERİ & İÇSEL RATING YÖNTEMLERİ

Akyıldız, Ahmet

Sermaye Piyasaları ve Finans

Tez Danışmanı:Doç.Dr.Hasan Eken

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2008 yılında başlayan ekonomik kriz ile birlikte tüm dünya ekonomileri resesyona girdi. Bu dönem itibariyle hem arz da yaşanan hem de talebe bağlı değişkenlik gösteren etmenlerinde etkisiyle bankaların borçlanma ve kredi verme yetilerinde ciddi değişimler oldu. Kredi kanallarında ve teminatlarda gerçekleşen bozulmalar neticesinde finansal para piyasaları derin bir yara almış ve yıkım derecesinde kötü sonuçlar ortaya çıkmıştır. Para piyasalarında yaşanan bu değişim neticesinde yatırımcılar ticari yatırım kağıtlarından çıkarak daha güvenli yatırım piyasalarına yönelmiş bu da para döngüsünün kaosa sürüklenmesine sebep olmuştur. Bu bağlamda yaşanan bu kriz ile yüzleşen insanların finansal sorumlulukları su yüzüne çıkmış, finansal hususlardaki yaşanan varlık erimesi yaşamlarını direk etkilemiştir.

Tüm dünya işte bu süreçte nereye varacağı bilinmeyen bir duruma gitmiş ve borçlanabilme yetisinde zararlar oluşmuştur. Bu zarar ciddi manada bankacılık faaliyetlerindeki etkilemiştir. Kağıt üzerinde uygulanan risk yönetimi faaliyetleri gerçek olarak uygulanamamış , finans devlerinin borçlulukları gün ve gün artmaya devam etmiştir.

Bu bağlamda bende krediler yönetimi ve kredi türleri, kredi derecelendirme, kredi risk yönetimi, skora ve süreçleri, ayrıştırma fonksiyonları, kredilendirme süreçlerinde doğrusal regresyon modelleri, kredi ölçüm teknikleri, geri ödeyememe risklerini anlatmaya çalıştım. Çalışmam içerisinde üstel dönüşümler, niceleyici model & nitelik modellerinin ölçümlemesini ve kalibrasyonunu, kredi modellemelerini açıklayarak bunun Türk bankacılık sistemi içerisindeki kredi portföy riskine, kredi risk modellerine ve rating bileşenlerine etkisini anlattım.

Anahtar Kelimeler: Kredilendirme, risk yönetimi, kredi riski, modellemeler, içsel rating,

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ABBREVIATIONS

Banking Regulation and Supervision Agency	: BRSA
Banks For International Settlement	: BIS
Central Bank of the Republic of Turkey	: CBRT
Credit Default Swap	: CDS
Credit Suisse Financial Products	: CSFP
Export Credit Agencies	: ECA
External Credit Assessment Institution	: ECAI
High-Volatility Commercial Real Estate	: HVCRE
International Money Fund	: IMF
Internal Rating Based	: IRB
Large And Complex Banking Group	: LCBG
Loss Given Default	: LGD
London Interbank Offer Rate	: LIBOR
Standart And Poor's	: S&P
Social Securities Foundation	: SSK
The Basel Committee on BankSupervision	: BCBS
The Multi-State Latent Factor Intensity	: MLFI

1.INTRODUCTION

At the root of the market failure that led to the current crisis was optimism bred by a long period of high growth and low real interest rates and volatility, together with a series of policy failures. These failures raise important medium run challenges for policymakers. With respect to financial policies, the task is to broaden the perimeter of regulation and make it more flexible to cover all systemically relevant institutions.

Additionally, there is a need to develop a macroprudential approach to both regulation and monetary policy. International policy coordination and collaboration need to be strengthened, including by better early-warning exercises and a more open communication of risks.

The broad retrenchment of foreign investors and banks from emerging economies and the resulting buildup in funding pressures are particularly worrisome. New securities issues have come to a virtual stop, bank-related flows have been curtailed, bond spreads have soared, equity prices have dropped, and exchange markets have come under heavy pressure. Beyond a general rise in risk aversion, this reflects a range of adverse factors, including the damage done to advanced economy banks and hedge funds at last.

The core of the problem is that as activity contracts across the globe, the threat of rising corporate and household defaults will imply still-higher risk spreads, further falls in asset prices, and greater losses across financial balance sheets. The risks of systemic events will rise, the tasks of restoring credibility and trust will be complicated, and the fiscal costs of bank rescues will escalate further.

The analysis has benefited from different kind of report and datas - I tried to explain financial conditions in the mature markets and Turkey underlying credibility and rating methods.

2.BANKING AND CORPORATE VALUATION SYSTEMS

2.1 VALUATION - SIMULATION WITH PD-LGD CORRELATION

Credit risky instruments can be valued using risk-neutral valuation techniques. Typically, the systematic risk associated with default probability is accounted for using a risk adjustment to instrument value. However, before the PD-LGD models were developed, risk adjustment was not usually associated with recovery. This methodology resulted from the assumption that there is no systematic risk in recovery. In a stressed LGD model, the MTM value is reduced due to the increase in LGD. Nevertheless, there is no guarantee that the amount of decrease is in-line with the systematic risk in recovery. As such, it may not be appropriate to use stressed LGD models for valuation purposes.

In contrast, the Moody's Analytics PD-LGD correlation model provides a granular framework that computes value and risk in an internally consistent manner. Levy and Hu (2006) show that the expected recovery under risk-neutral and physical measure has the following relationship:

$$E_0^Q[RR_T | A_T = DP_T] = E_0^P[RR_T | A_T = DP_T] \cdot \alpha_{0,T} \quad (2.1)$$

The MTM value of a credit instrument will decrease due to the additional discount of recovery. More generally, the expected value at any time after the analysis date, and in particular the expected value at horizon, will also drop. The expected spread will become wider to compensate for the systematic risk in recovery.

The positive correlation between PD and LGD will also change the shape of value distribution at horizon. In particular, PD-LGD correlation increases the variation of value given non-default.

When PD and LGD are assumed to be independent, the expected recovery amounts from a future default event are identical regardless of the credit quality of the instrument at horizon. If we assume that PD and LGD are positively correlated, this correlation will drive expected recovery up for good credit states and down for bad credit states.

Under the PLC model, the random LGD in each trial is drawn from a particular conditional distribution that is determined by the realization of systematic factors and idiosyncratic shocks of asset return. The correlation between PD and LGD can be accounted for by using either a more conservative value for LGD (i.e., a downturn or stressed LGD), or by extending the correlation structure and explicitly modeling the PD-LGD correlation.

The model provides a granular framework that computes risk and value in a consistent manner. The model utilizes Moody's Analytics LossCalc and GCorr data to overcome key challenges in parameterization. Numerical tests show that portfolio value decreases and risk, such as UL and capital, increases after accounting for PD-LGD correlation. The impacts of PD-LGD correlation depend upon portfolio characteristics such as PD, maturity, and asset R-squared.

2.2 VALUATION OF CORPORATE LOANS: A CREDIT MIGRATION

APPROACH

Since the early 1990's, the loan markets have seen tremendous growth in the liquidity of both loans and derivatives that are tied to loans. One element of this growth has been a rapid expansion in the secondary market for leveraged loans. Other elements include the growth of derivatives that are tied to loans the growth of structured products with loans in the underlying collateral pool and finally indices of loan derivatives that can form the basis of synthetic structured products.

Increasingly, multiple instruments are available to hedge loans, and the value of a specific loan is today much more likely to be directly observable.

The liquidity of the hedging instruments makes it convenient to mark them to market. Marking the hedging instruments to market, but not marking the loan can lead to accounting distortions. For example, if credit quality of a name declined, the value of the hedge would increase while the accounting value of the loan would remain constant, and it would look as though the bank had made a profit from the decline in the credit quality of one of their borrowers.

These distortions give rise to both the desire to be able to mark to market loans and the need for a credible methodology to do so. Loans are different from bonds in several important ways. The first is that most loans are floating rate instruments. Consequently, their value is not highly sensitive to changes in interest rates. Second, loans are typically prepayable.

For loans, an improvement in credit quality is a principal driver of the prepayment decision. Consequently, a model of credit migration is required to credibly model the embedded option features in loans. Many bonds are callable and many bond investors have computed an option-adjusted spread on such bonds for many years now. Nevertheless, this option is different from the option found in loans.

Examples of conditions within loan agreements include pricing grids that tie the spread on the loan to various measures of credit quality, such as an agency rating or a set of financial ratios, prepayment penalties, and options to use an alternative base (LIBOR or Prime) for the pricing resets.

In addition, there can be covenants that affect term, and collateral that should impact recovery levels. Revolving lines of credit have commitment amounts, usage fees (a drawn spread), commitment fees (a non-usage fee), and facility fees. Partly as a result of this form of structuring, in the event of default, a loan will typically have a better recovery than a bond. A credible methodology for marking a loan to market needs to account for all of these features.

In September 2006, the Financial Accounting Standards Board issued Statement No. 157, which establishes a framework for fair value accounting in the context of generally accepted accounting principles (GAAP) when fair value accounting is either permitted or required. The statement establishes a hierarchy of valuation methodologies. The hierarchy gives first priority to using actual prices for identical assets in active markets when available for establishing a fair market value

Second priority is valuation methodologies that are based on inputs that include a combination of prices from inactive markets on identical assets, prices of similar assets from active markets combined with observable characteristics of the asset, and finally market-corroborated inputs .The lost priority is given to unobservable inputs. These include the firm's own assumptions regarding how the market would view a particular asset re it to trade.

The Moody's KMV Credit Mark methodology—first introduced to the market in 2002 values a loan utilizing. The empirical work of this paper demonstrate how CreditMark can effectively value a loan using predominantly comparing the model prices to the actual prices on traded loans when available. The start point for CreditMark is the term structure of what call clean spreads.

A clean spread is what the spread would be on a zero-recovery, zero-coupon bond if it were to trade. These spreads can be populated from CDS spreads or bond spreads on the same name should they exist, or alternatively from spreads on names with comparable EDF™ credit measures, agency ratings, or internal ratings, as desired.

From the term structure of zero-recovery, zero-coupon bonds, CreditMark values the loan using a model of credit migration, a forward LIBOR curve, the terms of the loan, the paradigm of risk-neutral pricing, and recursive methods.

The modeling of a prepayment option is based on the borrower exercising the option when it is in their best interest under the terms of the loan and a specified transaction cost. The modeling of the usage of a revolver is based on a userprovided.

The model of credit migration is derived from a long history of firms with publicly trade equity. Credit migration model is derived from transition matrices that are based on a volatility-adjusted measure of market leverage (distance-to-default).

2.3 LOAN VALUATION BASICS

Simple term loan that pays a coupon plus LIBOR, the value of the loan can be written in the following way

$$P_t = \frac{QDF_t(1-LGD) + (1-QDF_t)(c + LIBOR + E^Q(P_{t+1} | no\ default))}{1+r} \quad (2.2)$$

where P_t is the price of the loan today, QDF_t is the risk-neutral probability of default over the next period, LGD is the risk-neutral loss given default, $c + LIBOR$ are the payments made on the loan over the next period, r is the risk free rate and $E^Q(P_{t+1} | no\ default)$ is the expected value of the loan (computed under the risk-neutral measure) at the end of the next period given that the obligor did not default and that the payments have been made.

Written this way, the value of the loan is decomposed into the discounted value in two states of the world: default and non-default. The value of the loan in default is equal to the discounted value of $1-LGD$. The value of the loan in the non-default state is equal to the sum of the discounted value of the coupon plus LIBOR, plus the value of the loan after these payments have been made. The value of the loan today is the value of the sum of the value of these two states, weighted by their respective probabilities under the risk-neutral measure.

With a simple induction argument, one can show that the price of the loan remains constant at par if the coupon, c , is equal to the risk-neutral expected loss. It is useful to express the value of the loan in terms of a second-order Taylor expansion:

For the valuation of loans with various embedded contingent claims characterizing the credit migration of the borrower at different horizon dates. Many practitioners will use agency ratings to represent credit states and a Markov chain model based on a rating transition matrix to characterize the credit migration. Migration framework, in contrast, proxies for the firm's underlying credit risk with a volatility-adjusted measure of leverage (its distance to default).

However, that while the concept of a borrower's Distance to Default (DD) comes out of a structural model of default risk (Moody's KMV Vasicek-Kealhofer (VK) model) an EDF measure of default risk is not required to value a loan. Valuation can be based on the CDS or Bond spread of the name, the RiskCalc EDF, the agency rating or even the bank's internal rating for the obligor associated with a specific loan.

As DD values computed from the structural model are continuous, need to divide them into a finite number of DD buckets to take advantage of the ease of discrete-state modeling. Model of the evolution of discretized DD values as a Markov chain. Because this evolution can be graphically represented by a DD lattice refer modeling approach as the lattice model.

The migration probabilities in the lattice to match the realized migration rates obtained from a large historical database of DD migrations.

Loans are structured in many different ways. Terms loans pay a coupon on top of a floating interesting rate for a specified period of time, but the borrower has the option to prepay. Revolvers are lines of credit for which the borrower pays a usage fee and a facility fee. Revolvers can be canceled. There are pricing grids and term out options. Sometimes there is a prepayment penalty associated with a prepayment option. To rigorously model these options, a concept of credit migration is required.

3. CREDIT AND RISK MANAGEMENT

3.1. DEFINITION OF CREDITS

As defined as article 48, Banking Law In Turkey, cash credits given by Banks and non-cash credits issued by the banks such as letters of guarantee, counter guarantees, sureties, aval, endorsment, acceptance and undertakings and similar capital market instruments, funds lent by means of depositing or by any other means, receivables arising out of forward sales of assets, overdue cash credits, interests which have accrued, yet have not been collected, amounts of non-cash credits which have become cash, receivables due from reverse repo transactions, risk undertaken due to futures and option agreements and the other similar agreements, partnership shares and transactions defined as credits.

3.2. CREDIT TYPES & CASH CREDITS

Cash credits types made available for institutions categorized according to disbursement and manner and purpose and main cash credit limits types.

3.2.1 Cash Credits (Domestic Currency)

A type of limit aimed at meeting short term finance needs of clients. Its essential that term be longer than 1 year at the first disbursement. Of these credits, principal collection is essential at maturity dates and interest collection is essential at the interest payment period.

3.2.3. Spot Credits & Interim Payment

This type of account is selected in the event clients demands credit with fixed interest rate and term. Interest rate changes and interim payments are not made in these types of credits. Principal and interest are collected at the maturity date pre-set and credit is closed.

A type of credit account that is operated in a manner where certain amount of credit is made available at once and repayment are made at desired intervals and amounts until maturity date.

3.2.4. Cash / Foreign Exchange / Eximbank Credit TL / FX

A type of limit used in the off shore banking and free zones. Like cash credits (If you live in Germany EURO, or in the Turkey cash credits Turkish Liras.)

Foreign exchange credit is a type of credit with a term of 18–24 months disbursed to persons residing in domestic country (such as in Turkey) for financing export, sales and deliveries deemed export as ll as operations causing income in foreign currency.

Credits which are provided by Eximbank for disbursement to exporter companies and exporters that are manufacturers as well as manufacture companies that produce goods for export in return for undertaking of export by means of state in order to incentives the companies for export and help national economy develop and of which disbursement terms that are determined by regulators (Eximbank). Credit is disbursed through commercial banks within the limit allocated by Eximbank to every bank.

3.2.5. Middle L/T Import Financing / Overdraft Account Financing Of Supplier

Engage with business abroad within framework of the permits obtained, for purpose of financing operations such as contracting service abroad, sale shops outside the customer line, sea transportations in international waters, land transportations, air transportations.

Credits disbursed in the form of overdraft account by defining the same to account of client. Manner of disbursement, interest rate, interest collection details arrange by creditors.

This a product which finances the parent companies with strong financial structure for the deferred payments they will make for the goods/services they have purchased from market.

3.2.6. Special / Permitted - Legal Payment Blocked Drawing Cheque Credit

Disbursed by means sending cheques of client which be collected through bank system clearing and crediting a certain percentage to client account on the same day by taking into consideration efficiency of client/company.

In the order to pay delayed or permits obtain legal payments such as S.S.K (Social Securities Foundation) or other taxes clients are obliged to pay to be credited and paid by bank.

A credit type that is disbursed in line with needs of clients by issuing of drawing cheque by banks, crediting and blocking its amount. This credit re-open blocking credit lines clearing same day. Their supplier by way of taking over their deferred payments providing cost effective financing on easy terms for the relevant suppliers.

3.2.7. Cheque Credits

This type of credit can be assign by law such as “law defines as the amount banks are obligated to pay for bad cheques as of 20.01.2010 as 500 TL”. Such amount may be changed every year. So this credit follod like as non-credit cash.

Credits With Installment ;

- i) Consumer Credits
- ii) Car Credits
- iii) Housing Credits

3.3 NON-CASH CREDITS

3.3.1. Letter Of Credits / Sight Letter Of Credit

Letter of credit is a bank undertaking as to the fact that a certain sum shall be paid to the seller of the goods and service, on the condition that required document showing the goods have been loaded or service has been fulfilled is submitted in the timely manner.

Credit of credit paid upon submission of document complying with conditions of letter of credit by issuing bank, confirming or advising bank based on the por granted by the issuing bank or any other bank within terms of letter of credits.

- i) Deferred Payment L/C

Deferred payment L/C to the beneficiary is made delivery of documents to the buyer, not upon submission of the documents. These types of letter of credits used for payment of sums payable for the goods subject to forward sale.

3.3.2 Acceptance Letter Of Credit / Mixed Payment Letter Of Credit

In case of forward sale, sums payable for the goods may be paid with letter of credit used with deferred policies called Acceptance L/C.

The only difference between acceptance letter of credit and deferred payment letter of L/C is addition of deferred policy by the seller to the documents submitted together with these L/C.

These are L/C types which are mixture of two types of letters of credit payable upon submission of documents or after submission there.

3.3.3 Derivatives Limit

- i) Swap Transactions
- ii) Forward Buy – Sell Transactions
- iii) Options Transactions
- iv) Futures Transactions

In other to main case pursuant to Banking Law In Turkey numbered 5411 “ Risk undertaken by the banks due to futures and option contract as the similar contracts are deemed credits regardless of account where they are monitored”.

3.3.4 Middle Term & Long Term Credits

Credits with a term ranging from 1–3 years generally segmented by middle term credits. Credits with a term longer than 3 years group in long term credits. Like as long term corporate or project credits.

3.4. CREDIT RISK MODELLING

Regulatory financial institution all around the world take steps against the crisis, decreasing interest rates, re-arrange spending programs, relaxing fiscal policy methods or discussing more rigorous supervisory processes and regulations. Especially recent years credibility one of the important issues for banks and financial institutions.

Credit risk management includes: modelling credit risk on a portfolio, credit risk provisioning, portfolio management, derivatives, capital allocation with economic risk existing regulatory capital regime manners under these circumstances.

An important consequence of the recent financial crisis and recession has been the ongoing wave of major corporate failures and near-failures: In the first eight months of 2009 216 corporate issuers defaulted affecting \$523 billion of debt (September 2009 S&P report). The leading indicator of the likelihood of failure used by investors and policymakers is the firms credit rating. Recently, credit ratings have been widely criticized for providing an inaccurate evaluation of credit quality.

Matthias P. Juttner from University of Zurich and Swiss Finance Institute explain the effectation of the last crisis with these words “Due to the subprime crisis financial institutions around the world have reported tremendous losses. Further consequences for all parts of the economy are entirely unforeseen.”

The key element is the computation of the distribution of aggregate credit portfolio losses. One of the crucial parameters is the expected loss (EL), which is defined as the product of three risk components: probability of default (PD), loss given default (LGD) and the exposure at default (EAD). The LGD describes the magnitude of likely loss on the exposure and is expressed as a percentage of the exposure.

Moreover, the loss is contingent upon the amount to which the bank was exposed to at the time of default, commonly expressed as EAD. Like in many credit risk models, also the rules of the Internal Rating-Based Approach (IRB approach) of the Basel Capital Accord are implicitly based on the assumption of independent LGD rates and default events. However, there is strong evidence of correlation between LGD's and default events.

For instance, the current decline of real estate prices has a positive impact on the LGD of loans which are secured by means of collaterals. The credit deterioration of a counterparty can trigger the credit deterioration of other counterparties through these inter-firm links. Beside common systematic factors, also the dependence between PD and LGD can be established by firm interdependence.

Like an as the lower recovery rate of firm name A implies ceteris paribus a higher PD of the counterparty firm B. In the case that firm A defaults, only a smaller fraction of the amount of outstanding receivables or debt can be reimbursed, which weakens the financial condition of firm B and therefore increases the PD of the firm. At the bottom line, PD and LGD are time-varying and are effected by common systematic factors. Inter-firm links can create correlated PDs and can also establish the dependence between the risk components.

Credit risk can be defined as the potential that a borrower or counterparty will fail to meet its obligations in accordance with the terms of an obligation's loan agreement, contract or indenture. Banks need supplemental credit assessments because they frequently lend to unrated firms.

However, since a bank's individual exposures to such firms are often relatively small, it is typically uneconomical for borrowers to obtain Moody's rating or for banks to devote extensive internal resources to the analysis of a particular borrower's credit quality. Not surprisingly, these economic factors have caused banking institutions to be among the earliest adopters of quantitative credit risk models.

Many credit risk models have been proposed in the literature. They are usually categorized into “structural-form” models and “reduced-form” models. Within Merton’s framework, structural-form models focus on constructing the distribution of a firm’s asset value and estimating its probability of default (later denoted as PD) and recovery rate (later denoted as RR). A firm’s asset value distribution is derived from equity market value through an option-based theory.

Table No: 3.1 Credit Risk Measurement

CREDITRISK +			
Credit Risk Measurement		Economic Capital	Applications
Exposures	Default Rates	Credit Default Loss Distribution	Provisioning
Recovery Rates	Default Rate Volatilities	Scenario Analysis	Limits
CREDITRISK + Model			Portfolio Management

Source: Copyright ©1997 Credit Suisse First Boston International Credit Risk+

3.5 CAPITAL REQUIREMENTS FOR CREDIT RISK MEASURES

3.5.1 Credit Risk – The Standardised Approach

It is now certain that the standardised approach will be adopted by a large number of banks, not necessarily located in low-income countries and emerging markets such as Turkey. According to a survey of 294 financial institutions from 38 countries conducted in late 2003, 35 percent of total respondents (30 percent of European respondents) planned to opt for this simpler approach to credit risk (KPMG, 2004). Compared to previous years, these percentages are much higher because banks appear to have realised the significant level of effort required to comply with the IRB.

Moreover, the uncertainty surrounding regulators' approach to capital relief is forcing some banks to reconsider their decision to adopt the advanced approaches to credit risk. The banks which will most likely adopt the standardised approach in Europe are non-quoted banks, some quoted banks and the vast majority of banks belonging to the mutual sector.

The standardised approach uses external ratings such as those provided by external credit assessment institutions to determine risk-weights for capital charges, whereas the IRB allows banks to develop their own internal ratings subject to the meeting of specific criteria and supervisory approval. While large internationally active banks should opt for the IRB, the vast majority of small and medium-sized credit institutions from the G-10 are expected to adopt the simpler standardised approach.

From the very beginning, the 1988 Accord was subject to criticism, which was hardly surprising in view of the fact that the agreement had to accommodate banking practices and regulatory regimes in countries with varied legal systems, business norms and prevalent institutional structures. Criticisms were mainly directed at its failure to make adequate allowance for the degree of reduction in risk exposure achievable through diversification and at its arbitrary and non-discriminatory calibration of certain credit risks

The uniform weight attributed in almost all circumstances to private borrowers, regardless of their creditworthiness was considered an incentive to regulatory arbitrage, under which banks were tempted to exploit the opportunities afforded by the Accord's classification of risk exposure to increase their holding of high-yielding, but also high-risk assets.

3.5.2 External Credit Assessment

Basel committee say to banks a choice broad methodologies for calculating their capital requirements for credit risk. But all of these items are constructive suggestion for financial institutions. We can not talking about legitimative reasons for punishing banks and groups. These fundamental assessment established keen on supervisory agency for credit assessment and capital activity. So one alternative will be to measure credit risk in a standardised manner, supported by external credit assessments.

Table no: 3.2 External Credit Assessments

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk Weight	0%	20%	50%	100%	150%	100%

Source: International Convergence of Capital Measurement and Capital

Standards Bank for International Settlements Press & Communications

CH- 4002 Basel, Switzerland

At national discretion, a lower risk ight may be applied to banks' exposures to their sovereign (or central bank) of incorporation denominated in domestic currency and funded in that currency.

Where this discretion is exercised, other national supervisory authorities may also permit their banks to apply the same risk weight to domestic currency exposures to this sovereign (or central bank) funded in that currency. For the purpose of risk weighting claims on sovereigns, supervisors may recognise the country risk scores assigned by Export Credit Agencies (ECA's). To qualify, an ECA must publish its risk scores and subscribe to the OECD agreed methodology.

Banks may choose to use the risk scores published by individual ECA's that are recognised by their supervisor, or the consensus risk scores of ECA's participating in the "Arrangement on Officially Supported Export Credits". The OECD agreed methodology establishes weight risk score categories associated with minimum export insurance premiums. These ECA risk scores will correspond to risk ight categories as detailed below.

Table no: 3.3 Credit Assessment Of Risk ight

ECA risk scores	0-1	2	3	4 to 6	7
Risk weight	0%	20%	50%	100%	150%

Source: International Convergence of Capital Measurement and Capital

Standards Bank for International Settlements Press & Communications

CH-4002 Basel, Switzerland

There are two options for claims on banks. National supervisors will apply one option to all banks in their jurisdiction. No claim on an unrated bank may receive a risk ight lor than that applied to claims on its sovereign of incorporation. Under the first option, all banks incorporated in a given country will be assigned a risk ight one category less favourable than that assigned to claims on the sovereign of that country.

However, for claims on banks in countries with sovereigns rated BB+ to B- and on banks in unrated countries the risk weight will be capped at 100 percent. The second option bases the risk weighting on the external credit assessment of the bank itself with claims on unrated banks being risk-ighted at 50 percent. Under this option, a preferential risk ight that is one category more favourable may be applied to claims with an original maturity of three months or less, subject to a floor of 20 percent. This treatment will be available to both rated and unrated banks, but not to banks risk ighted at 150 percent.

Table no : 3.4 Credit Assessment Of Banks

Option 1

Credit assessment of Sovereign	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk weight under Option 1	20%	50%	100%	100%	150%	100%

Option 2

Credit assessment of Banks	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk weight under Option 2	20%	50%	50%	100%	150%	50%
Risk weight for short-term claims ²² under Option 2	20%	20%	20%	50%	150%	20%

Source: International Convergence of Capital Measurement and Capital Standards Bank for International Settlements Press & Communications CH-4002 Basel, Switzerland Page:18

3.6. CORPORATE EXPOSURES IN CREDIT RISK

In general, a corporate exposure is defined as a debt obligation of a corporation, partnership, or proprietorship. Banks are permitted to distinguish separately exposures to small- and medium-sized entities (SME). Within the corporate asset class, five sub-classes of specialised lending (SL) are identified. Such lending possesses all the following characteristics, either in legal form or economic substance.

The exposure is typically to an entity (often a special purpose entity (SPE) which was created specifically to finance and/or operate physical assets; The borrowing entity has little or no other material assets or activities, and therefore little or no independent capacity to repay the obligation, apart from the income that it receives from the asset(s) being financed.

IFRS 7 The objective of this IFRS is to require entities to provide disclosures in their financial statements that enable users to evaluate:

- i) the significance of financial instruments for the entity's financial position and performance; and
- ii) the nature and extent of risks arising from financial instruments to which the entity is exposed during the period and at the reporting date, and how the entity manages those risks. The qualitative disclosures describe management's objectives, policies and processes for managing those risks. The quantitative disclosures provide information about the extent to which the entity is exposed to risk, based on information provided internally to the entity's key management personnel. Together, these disclosures provide an overview of the entity's use of financial instruments and the exposures to risks they create.

The terms of the obligation give the lender a substantial degree of control over the asset(s) and the income that it generates; and As a result of the preceding factors, the primary source of repayment of the obligation is the income generated by the asset(s), rather than the independent capacity of a broader commercial enterprise.

The five sub-classes of specialised lending are project finance, object finance, commodities finance, income-producing real estate, and high-volatility commercial real estate. Each of these sub-classes is defined below.

i) Project Finance

Project finance (PF) is a method of funding in which the lender looks primarily to the revenues generated by a single project, both as the source of repayment and as security for the exposure. This type of financing is usually for large, complex and expensive installations that might include, for example, por plants, chemical processing plants, mines, transportation infrastructure, environment, and telecommunications infrastructure.

Project finance may take the form of financing of the construction of a new capital installation, or refinancing of an existing installation, with or without improvements.

In such transactions, the lender is usually paid solely or almost exclusively out of the money generated by the contracts for the facility's output, such as the electricity sold by a power plant. The borrower is usually an SPE that is not permitted to perform any function other than developing, owning, and operating the installation. The consequence is that repayment depends primarily on the project's cash flow and on the collateral value of the project's assets. In contrast, if repayment of the exposure depends primarily on a well established, diversified, credit-worthy, contractually obligated end user for repayment, it is considered a secured exposure to that end-user.

ii) Object Finance

Object finance (OF) refers to a method of funding the acquisition of physical assets (e.g. ships, aircraft, satellites, railcars, and fleets) where the repayment of the exposure is dependent on the cash flows generated by the specific assets that have been financed and pledged or assigned to the lender. A primary source of these cash flows might be rental or lease contracts with one or several third parties. In contrast, if the exposure is to a borrower whose financial condition and debt-servicing capacity enables it to repay the debt without undue reliance on the specifically pledged assets, the exposure should be treated as a collateralised corporate exposure.

iii) Commodities Finance

Commodities finance (CF) refers to structured short-term lending to finance reserves, inventories, or receivables of exchange-traded commodities (e.g. crude oil, metals, or crops), where the exposure will be repaid from the proceeds of the sale of the commodity and the borrower has no independent capacity to repay the exposure.

This is the case when the borrower has no other activities and no other material assets on its balance sheet.

The structured nature of the financing is designed to compensate for the weak credit quality of the borrower. The exposure's rating reflects its self-liquidating nature and the lender's skill in structuring the transaction rather than the credit quality of the borrower.

The Committee believes that such lending can be distinguished from exposures financing the reserves, inventories, or receivables of other more diversified corporate borrowers. Banks are able to rate the credit quality of the latter type of borrowers based on their broader ongoing operations. In such cases, the value of the commodity serves as a risk mitigant rather than as the primary source of repayment. Income-producing real estate, income-producing real estate (IPRE) refers to a method of providing funding to real estate (such as, office buildings to let, retail space, multifamily residential buildings, industrial or warehouse space, and hotels) where the prospects for repayment and recovery on the exposure depend primarily on the cash flows generated by the asset. The primary source of these cash flows would generally be lease or rental payments or the sale of the asset. The borrower may be, but is not required to be, an SPE, an operating company focused on real estate construction or holdings, or an operating company with sources of revenue other than real estate.

The distinguishing characteristic of IPRE versus other corporate exposure that are collateralised by real estate is the strong positive correlation between the prospect for repayment of the exposure and the prospects for recovery in the event of default, with both depending primarily on the cash flows generated by a property.

iv) High-Volatility Commercial Real Estate

High-volatility commercial real estate (HVCRE) lending is the financing of commercial real estate that exhibits higher loss rate volatility (higher asset correlation) compared to other types of SL. HVCRE includes: Commercial real estate exposures secured by properties of types that are categorised by the national supervisor as sharing higher volatilities in portfolio default rates;

Loans financing any of the land acquisition, development and construction (ADC) phases for properties of those types in such jurisdictions; and Loans financing ADC of any other properties where the source of repayment at origination of the exposure is either the future uncertain sale of the property or cash flows whose source of repayment is substantially uncertain (the property has not yet been leased to the occupancy rate prevailing in that geographic market for that type of commercial real estate)

Unless the borrower has substantial equity at risk. Commercial ADC loans exempted from treatment as HVCRE loans on the 50 basis of certainty of repayment of borrower equity. Where supervisors categorise certain types of commercial real estate exposures as HVCRE in their jurisdictions, they are required to make public such determinations. Other supervisors need to ensure that such treatment is then applied equally to banks under their supervision when making such HVCRE loans in that jurisdiction.

v) Definition Of Sovereign Exposures

This asset class covers all exposures to counterparties treated as sovereigns under the standardised approach. This includes sovereigns (and their central banks), certain PSEs identified as sovereigns in the standardised approach, MDB's that meet the criteria for a 0 percent risk ight under the standardised approach.

3.7 TYPES OF CREDIT RISK

There are two main types of credit risk:

- i) Credit spread risk: Credit spread risk is exhibited by portfolios for which the credit spread is traded and marked-to-market. Changes in observed credit spreads impact the value of these portfolios.
- ii) Credit default risk: All portfolios of exposures exhibit credit default risk, as the default of an obligor results in a loss.

3.7.1 Credit Spread Risk

Credit spread is the excess return demanded by the market for assuming a certain credit exposure. Credit spread risk is the risk of financial loss owing to changes in the level of credit spreads used in the mark-to market of a product.

Credit spread risk fits more naturally within a market risk management framework. In order to manage credit spread risk, a firm's value-at-risk model should take account of value changes caused by the volatility of credit spreads. Since the distribution of credit spreads may not be normal, a standard variance-covariance approach to measuring credit spread risk may be inappropriate. However, the historical simulation approach, which does not make any assumptions about the underlying distribution, used in combination with other techniques, provides a suitable alternative.

Credit spread risk is only exhibited when a mark-to-market accounting policy is applied, such as for portfolios of bonds and credit derivatives. In practice, some types of products, such as corporate or retail loans, are typically accounted for on an accruals basis. A mark-to-market accounting policy would have to be applied to these products in order to recognise the credit spread risk.

On the other hand some research focused on dynamic credit risk model especially preferences of these models focus on hazard rate of a company has a deterministic drift with periodic impulses. The impulse size plays a similar role to default correlation with credit risks and credit derivatives risks.

In a specific model the company or companies being modeled remain the same through time. In a general model they do not remain the same, but are defined to have certain properties. A model of the evolution of the credit spread for a particular company or the evolution of losses on a particular portfolio is a specific model.

Extensions of the Merton (1974) structural model provide one approach for developing a specific dynamic model. Correlated processes for the values of the assets of the underlying companies are specified and a company defaults when the value of its assets reaches a barrier. The most basic version of the structural model is very similar to the Gaussian copula model.

Extensions of the basic model have been proposed by Albanes (2005), Baxter (2006), and Hull (2005). Structural models have the advantage that they have sound economic underpinnings. Their main disadvantage is that they are difficult to calibrate to market prices and usually have to be implemented with Monte Carlo simulation.

Reduced-form models provide an alternative to structural models. The most natural reduced-form approach to developing a dynamic model is to specify correlated diffusion processes for the hazard rates of the underlying companies. This is because there is a limit to how high the correlation between times to default can become.

This has led researchers to include jumps in the processes for hazard rates. Duffie and Gârleanu (2001) for example assume that the hazard rate of a company is the sum of an idiosyncratic component, a component common to all companies, and a component common to all companies in the same sector.

Each component follows a process with both a diffusion and a jump component. Other reduced form approaches are provided by Chapovsky (2006), Graziano and Rogers (2005), Hurd and Kuznetsov (2005), and Joshi and Stacey (2006). Another approach to developing dynamic models involves the development of a model for the evolution of the losses on a portfolio. This is sometimes referred to as the “top down” approach. The behavior of individual companies in the portfolio is not considered.

Sidenius (2004) use concepts from the Heath, Jarrow, and Morton (1992) interest-rate model to suggest a complex general no-arbitrage approach to modeling the probability that the loss at a future time will be less than some level. Bennani (2005) proposes a model of the instantaneous loss as a percentage of the remaining principal. Schönbucher (2005) models the evolution of the loss distribution as a Markov chain. Errais (2006) suggest a model where the arrival rate of defaults experiences a jump when a default happens.

In Longstaff and Rajan (2006) the loss follows a jump process where there are three types of jumps: firm specific, industry, and economy-wide. Putyatin et al (2005) suggest a model where the mechanism generating multiple defaults resembles the kinetics of certain chemical reactions. Walker (2007) uses a dynamic discrete-time multi-step Markov loss model.

3.7.2 Credit Default Risk

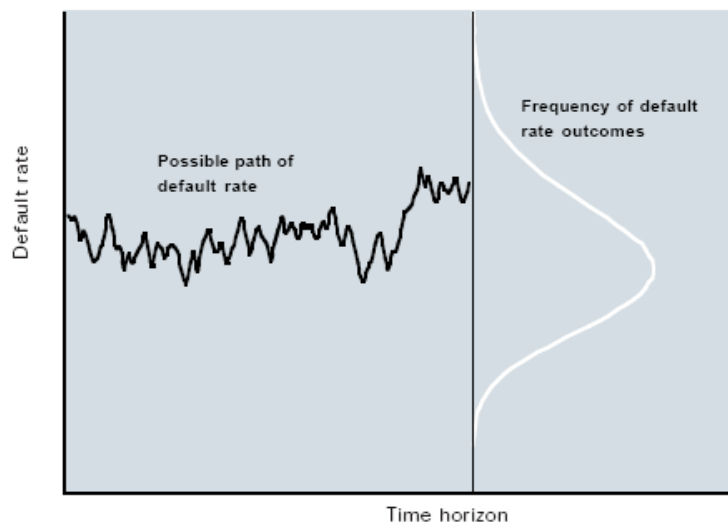
Credit default risk is the risk that an obligor is unable to meet its financial obligations. In the event of a default of an obligor, a firm generally incurs a loss equal to the amount owed by the obligor less a recovery amount which the firm recovers as a result of foreclosure, liquidation or restructuring of the defaulted obligor. All portfolios of exposures exhibit credit default risk, as the default of an obligor results in a loss.

When treated as a continuous variable, the possible default rate over a given time horizon is described by a distribution, which can be specified by a default rate and a volatility of the default rate.

The following figure illustrates the path that a default rate may take over time and the distribution that it could have over that time.

Table 3.5 Default Continuous Variables

► **Figure 2:**
Default rate as a
continuous random
variable



Source: CreditMetrics™—Technical Document New York April 2, 1997 Page:8

For in these terms default risk can assign by Black-Cox Model. In these expression new research given us cumulative probability of default and the relevant hazard rate shall given us same historical data and same default risk level.

The risk of default is largely due to the uncertainty in a time evolution of the firm's asset value. Behavior of many other determinants of the probability of default the value of firm's short- and long-term liabilities, L the volatility of its assets standard deviation, the expected rate of assets growth, the risk-free interest yield may be also unknown and complicate the analysis.

Starting with Merton's structural model of default, the time-behavior of is modeled as the geometric Brownian motion.

However, in reality default may happen before the maturity of the issuer's debt. This situation has been first addressed in the Black-Cox extension of the Merton's model. Black and Cox made two assumptions that are now common in the credit risk literature:

- i) an issuer may default at any time
- ii) default happens at the first passage, irreversibly, instantly, and at any contact,
- iii) whenever the diffusive path of hits the absorbing default barrier or some low threshold.

Further development of structural models in the first-passage approximation includes non-zero coupon bonds, stochastic interest rates, and endogenously defined default boundaries.

3.8. CREDIT RISK MEASURE TECHNIQUES

Developments in financial markets and national and international regulation, credit risk and therefore a lot of credit has increased the importance of stratification. In the financial sector ratings about relationships in general, a debtor's obligations can not fulfill the entire time all the analysis is determined.

Validation, the adequacy of rating systems, reliability of measurement, calibration of the model results by comparison with a known reference processes are needed to make corrections. Credit risk measure generally used in risk literature to characterize the credit risk standard deviation and percentile level. Credit risk model underlying both of these risk measures is the same in finance sector.

Standard deviation and percentile level risk measures reflect potential losses from the same portfolio distribution. However, they are different measures of credit risk. The credit risk in a portfolio arises because there is variability in the value of the portfolio due to credit quality changes and variability could be main indicator for measure risk level.

Credit risk model nowadays is an important part for financial engineering. For finding risk models and pre-structure modellism Fundamentals lays on these measurement.

David Lando says that “Credit risk modeling is a rapidly growing area of financial economics and financial engineering. Banks and other financial institutions are applying increasingly sophisticated methods for assessing the risk of their loan portfolios and their counterparty exposure on derivatives contracts.

These new markets and better data availability on the traditional corporate bond market have provided new laboratories for financial economists to test asset pricing theories, to look at capital structure decisions, and to understand financial innovation.

Table no: 3.6 Financial Product Reference Portfolio

Credit Swiss Financial Portfolio

(In percent)

Obligor exposure	Mean Default rate	Standard deviation of default rate	Factor weights					Total
			Sector 1	Sector 2	Sector3	Sector4		
358,475	30.00	15.00	50	30	10	10	100	
1,089,819	30.00	15.00	25	25	25	25	100	
1,799,710	10.00	5.00	25	25	20	30	100	
1,933,116	15.00	7.50	75	5	10	10	100	
2,317,327	15.00	7.50	50	10	10	30	100	
2,410,929	15.00	7.50	50	20	10	20	100	
2,852,184	30.00	15.00	25	10	10	55	100	
2,957,885	15.00	7.50	25	25	20	30	100	
3,137,989	5.00	2.50	25	25	25	25	100	
3,204,044	5.00	2.50	75	10	5	10	100	
4,727,724	1.50	0.75	50	10	10	30	100	
4,830,517	5.00	2.50	50	20	10	20	100	
4,912,097	5.00	2.50	25	25	25	25	100	
4,928,989	30.00	15.00	25	10	10	55	100	
5,042,312	10.00	5.00	25	25	30	20	100	
5,320,384	7.50	3.75	75	10	5	10	100	
5,435,457	5.00	2.50	50	20	10	20	100	
5,517,586	3.00	1.50	50	10	10	30	100	
5,764,596	7.50	3.75	25	25	20	30	100	
5,847,845	3.00	1.50	25	10	10	55	100	
6,466,533	30.00	15.00	25	25	20	30	100	
6,480,322	30.00	15.00	75	10	5	10	100	
7,727,651	1.60	0.80	25	25	20	30	100	
15,410,906	10.00	5.00	50	20	10	20	100	
20,238,895	7.50	3.75	75	10	10	5	100	

Source: IMF Working Paper Monetary and Financial Systems Department and Technology and General Services Department Review and Implementation of Credit Risk Models of the Financial Sector Assessment 2006. Program Prepared by Renzo G. Avesani, Kexue Liu, Alin Mirestean, and Jean Salvati Authorized for distribution by David D. Marston and John C. Johnson May

3.8.1 Credit risk measure: Standart Deviation

The standard deviation is a symmetric measure of dispersion around the average portfolio value. The greater the dispersion around the average value, the larger the Standard deviation, and the greater the risk. If the portfolio values are expressed in dollars, this standard deviation calculation also results in a dollar amount.

$$*Mean=p_1 \cdot V_1 + p^2 \cdot V^2 + \dots + p^{64} \cdot V^{64} \quad (3.1)$$

$$* (\text{Standard Deviation})^2 = p_1 \cdot (V_1 - \text{Mean})^2 + p^2 \cdot (V^2 - \text{Mean})^2 + \dots + p^{64} \cdot (V^{64} - \text{Mean})^2$$

(3.2)

Note that the above expression yields the squared standard deviation value, which is also known as the “variance.” The square-root of this value is the standard deviation. The individual terms in the expression are of the form $(V_i - \text{Average})$

3.8.2 Credit Risk Measure: Percentile Level

The interpretation of the percentile level is much simpler than the standard deviation: the lost value that the portfolio will achieve 1 percent of the time is the 1st percentile.

The particular level used is the choice of the portfolio manager, and depends mostly on how the risk measure will be applied. For normal distributions (or any other known distribution which is completely characterized by its mean and standard deviation), it is possible to calculate percentile levels from knowledge of the standard deviation. Unfortunately, normal distributions are mostly a characteristic of market risk. In contrast, credit risk distributions are not typically symmetrical or bell-shaped. In particular, the distributions display a much fatter tail than a standard bell-shaped curve. Since cannot assume that credit portfolio distributions are normal, nor can characterize them according to any other standard distribution, must estimate percentile levels via another approach.

To calculate a percentile level, must first specify the full distribution of portfolio values. For portfolios consisting of more than two exposures, this requires a simulation approach, which may be time-consuming.

4. CREDIT MODELING LITERATURE

4.1 INFRASTRUCTURE DEVELOPMENT OF STUDIES

This line of studies starts from Merton (1974) and evolves into two generations. The main difference between them is that the second-generation models relax the fixed debt assumption of original models.

The first generation includes Black and Cox (1976), Geske (1977), Vasicek (1984), Mason and Rosenfeld (1984), and Crouhy and Galai (1994). The second-generation models contain Kim, Ramaswamy and Sundaresan (1993), Nielsen, Saa-Requejo, Santa Calara (1993), Hull-White (1995), Longstaff and Schwartz (1995). Reduce-form model, on the other hand stresses the “non-asset-value related information”, such as credit rating and recovery rate. They estimate and price a firm’s credit risk by observable market credit spreads.

Credit risk is presumably the oldest risk type facing a bank: it is the risk that the originator of a financial product (a mortgage, say) faces as a function of the (in)capability of the obligor to honour an agreed stream of payments over a given period of time.

If only one had taken this question more seriously at the time. Modern product development, and the way credit derivatives and structured products are traded on OTC markets, have driven credit risk partly into the under ground of financial markets. One way of describing “under ground” for banks no doubt is “off-balance sheet”.

Also regulators are becoming increasingly aware of the need for a combined view on market and credit risk. A most recent manifestation of this fact is the new regulatory guideline (within the Basel II framework) for an incremental risk charge (IRC) for all positions in the trading book with migration/default risk.

Also, regulatory arbitrage drove the creativity of (mainly) investment banks to singular heights trying to repackage credit risk in such a way that the bank could get away with a minimal amount of risk capital.

Finally, excessive leverage allowed to increase the balance sheet beyond any acceptable level, leading to extreme losses when markets turned and liquidity dried up. Several quotes from the above article early on warned about possible (very) extreme events just around the corner.

As seem there generally two types of credit risk model have been studied in the literature. Black and Scholes (1973) and Merton (1974) one of the well known studies in this methodology. characterized the default time is the first hitting time of the firm's asset value to a given boundary determined by the firm's liabilities.

As such, if the firm's asset value process follows a diffusion, then the default time is usually a predictable stopping time.

The difficulties with the structural approach are twofold: first, the firm's asset value process is not directly observable, making empirical implementation difficult; and second, a predictable default time implies credit spreads should be near zero on short maturity debt. This second implication is well known to be inconsistent with historical market credit spread data.

As I mention before the important question is that “why does credit risk is very important for global market and finance? In the U.S.A and Europe there are a lot of research and studies about this manner. All these fundamental research occurred with loss or unexpected to prevail risk management. In the J.P Morgan creditmetrics documents says that “Traditionally, portfolio managers have relied on a qualitative feel for the concentration risk in their credit portfolios. Intuitive – but arbitrary – exposure-based credit limits have been the primary defense against unacceptable concentrations of credit risk.”

However, fixed exposure limits do not recognize the relationship between risk and return. A more quantitative approach such as that presented here allows a portfolio

manager to state credit lines and limits in units of marginal portfolio volatility. Furthermore, such a model creates a framework within which to consider concentrations along almost any dimension (industry, sector, country, instrument type, etc.).

Another important reason to take a portfolio view of credit risk is to more rationally and accountably address portfolio diversification. The decision to take on ever higher exposure to an obligor will meet ever higher marginal risk – risk that grows geometrically with the concentration on that name.

Conversely, similar additional exposure to an equally rated obligor who has relatively little existing exposure will entail less risk. Indeed, such names may be individually risky, but offer a relatively small marginal contribution to overall portfolio risk due to diversification benefits.

Finally, by capturing portfolio effects (diversification benefits and concentration risks) and recognizing that risk accelerates with declining credit quality, a portfolio credit risk methodology can be the foundation for a rational risk-based capital allocation process

As you see there risk is primarily diversified by risk and return and exposure is the main problem for understanding risk and return relationship in the risky market. For making a good deal between these uncertainties there are good processes for segmentation.

- i) Financial products have become more complex. The growth of derivatives activity has created uncertain and dynamic counterparty exposures that are significantly more challenging to manage than the static exposures of more traditional instruments such as bonds or loans. End-users and providers of these instruments need to identify such exposures and understand their credit, as well as related market, risks.
- ii) The proliferation of credit enhancement mechanisms: third-party guarantees, posted collateral, margin arrangements, and netting, makes it increasingly necessary to assess credit risk at the portfolio level as well as at the individual exposure level.

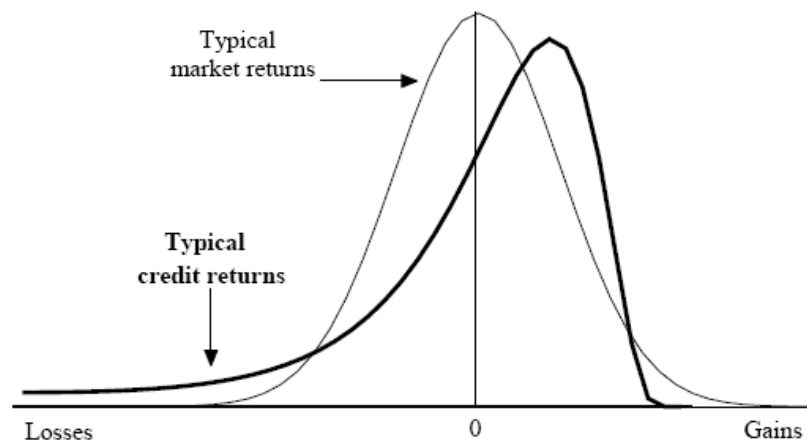
- iii) Improved liquidity in secondary cash markets and the emergence of credit derivatives have made possible more active management of credit risk based on rational pricing. Proper due diligence standards require that institutions thoroughly review existing risks before hedging or trading them.

- iv) Innovative new credit instruments explicitly derive value from correlation estimates, or credit events such as upgrades, downgrades or default. can best understand these in the context of a portfolio model that also explicitly accounts for credit quality migration

Table no: 4.1 Comparison Of Distrubition Credit Market Returns

Chart 1.1

Comparison of distribution of credit returns and market returns



Source: CreditMetrics™—Technical Document page:7

4.2 CREDIT VALUATION MODELS

4.2.1 Merton Model

Merton (1974) makes use of the Black and Scholes (1973) option pricing model to value corporate liabilities. This is a straightforward application only if we adapt the firm's capital structure and the default assumptions to the requirements of the Black-Scholes model. Let us assume that the capital structure of the firm is comprised by equity and by a zero-coupon bond with maturity T and face value of D , whose values at time t are denoted by E_t and $z(t, T)$ respectively, for $0 \leq t \leq T$. The firm's asset value V_t is simply the sum of equity and debt values.

Under these assumptions, equity represents a call option on the firm's assets with maturity T and strike price of D . If at maturity T the firm's asset value V_T is enough to pay back the face value of the debt D , the firm does not default and shareholders receive $V_T - D$. Otherwise ($V_T < D$) the firm defaults, bondholders take control of the firm, and shareholders receive nothing. Implicit in this argument is the fact that the firm can only default at time T . This assumption is important to be able to treat the firm's equity as a vanilla European call option, and therefore apply the Black-Scholes pricing formula.

The intuition is from Merton (1974) the delta function and pricing equation link equity volatility and credit spread directly to the structural variables and parameters. With these identifying restrictions, we can build an internally consistent GMM estimator (Hansen, 1982), which minimizes the fitted errors of credit spreads and equity volatility, with an appropriate weighting matrix determined by the pricing model and data sample. Along with consistent parameter estimation, we obtain an omnibus specification test, to rank order various credit risk models and to judge their pricing performance in a systematic framework.

In addition also use the term structure and time series of CDS spreads to evaluate the economic pricing errors, which should by-and-large confirm our GMM specification test results. A structural model would be rejected by the GMM criterion function test, if the pricing errors are relatively large and exhibit systematic variations, assuming that the equity and credit markets are efficient. The implementation of our estimation strategy has several advantages.

First, use high frequency equity returns to construct a more accurate estimate of the equity volatility, there fore minimizing the measurement error imputed into the asset volatility estimate (given any structural model for the underlying asset process), while leaving the main suspect to possible model misspecification which really care about. Second, use the CDS spreads as a relative purer measure of the credit risk, therefore sanitizes our approach from the specific pricing error problem associated with bond market iniquity or other non-default characteristics (Longsta, Mithal, and Neis, 2005).

In addition,use the term structure and time series of CDS spreads in both estimation and pricing exercise, while holding constant the model specification and parameter values, thus avoiding the rolling sample extraction approach that is inconsistent with economic assumption underlying the structural models.

The rest of assumptions Merton (1974) adopts are the inexistence of transaction costs, bankruptcy costs, taxes or problems with indivisibilities of assets; continuous time trading; unrestricted borrowing and lending at a constant interest rate r ; no restrictions on the short selling of the assets; the value of the firm is invariant under changes in its capital structure (Modigliani-Miller Theorem) and that the firm's asset value follows a diffusion process. The firm's asset value is assumed to follow a diffusion process given by where σV is the (relative) asset volatility and W_t is a Brownian motion.

The main advantage of Merton's model is that it allows to directly apply the theory of European options pricing developed by Black and Scholes (1973). But to do so the model needs to make the necessary assumptions to adapt the dynamics of the firm's asset value process, interest rates, and capital structure to the requirements of the Black-Scholes model. There is a trade off between realistic assumptions and ease of implementation, and Merton's model opts for the latter one.

All extensions to this model introduce more realistic assumptions trying to end up with a model not too difficult to implement and with closed, or at least numerically feasible, solutions for the expressions of the debt value and the default probabilities. Merton himself (Merton 1974) presents some extensions to the model, in order to account for coupon bonds, callable bonds, stochastic interest rates, and relaxing the assumption that the Modigliani-Miller Theorem holds.

One problem of Merton's model is the restriction of default time to the maturity of the debt, ruling out the possibility of an early default, no matter what happens with the firm's value before the maturity of the debt. If the firm's value falls down to minimal levels before the maturity of the debt but it is able to recover and meet the debt's payment at maturity, the default would be avoided in Merton's approach.

4.2.1.1 Credit Risk Incomplete Information Model

Incomplete information is at the heart of information-based credit risk models. The first generated by a time change of filtrations and the second by finitely many marked point processes. This notion unifies the noisy information in Dufie and Lando and the partial information in Collin-Dufresne under which structural models are translated into reduced-form intensity-based model. Two types of credit risk models have been studied in the literature: structural and reduced-form. Structural models view a firm's liabilities as complex put options on the firm's assets.

Therefore, modeled in this approach are the firm's liability structure and the firm's asset value process. This methodology originated with Black and Scholes (1973) and Merton (1974). In these models, the default time is usually characterized as the first hitting time of the firm's asset value to a given boundary determined by the firm's liabilities. As such, if the firm's asset value process follows a diffusion, then the default time is usually a predictable stopping time.

The difficulties with the structural approach are twofold: first, the firm's asset value process is not directly observable, making empirical implementation difficult; and second, a predictable default time implies credit spreads should be near zero on short maturity debt. This second implication is well known to be inconsistent with historical market credit spread data.

Regarding incomplete information, the following two well-known cases are instrumental: the noisy and discrete accounting information in Duffie and Lando and the delayed information from continuous observations in Collin-Dufresne. It shall incorporate both the continuous and discrete nature of these information into notion of delayed filtration. Intuitively, a continuously delayed filtration allows information to show in continuously, albeit following a timeclock slower than the ordinary one. A discretely delayed filtration, on the other hand, does not allow new information to flow in between two consecutive observation times.

In contrast, the reduced-form approach was developed precisely to avoid modeling the firm's unobservable asset value process. This approach was originated by Jarrow and Turnbull (1992,1995), Artzner and Delbaen (1995), and Duffie and Singleton (1999). Typically, reduced-form models characterize default as the first jump time of a point process, often a Cox process (a doubly stochastic Poisson process). As such, the default time is usually a totally inaccessible stopping time, implying non-zero credit spreads for short maturity debt. A review of the credit risk literature can be found in many good books, including Ammann (2001), Bielecki and Rutkowski (2002), Duffie and Singleton (2003), Schaubucher (2003), and Lando (2004). A systematic study of the mathematical techniques used in reduced-form models is available in Elliott, Jeanblanc, and Yor (2000) and Jeanblanc and Rutkowski (2002).

As implied by the above description, structural and reduced-form models are viewed as competing paradigms. However, recent work by Duffie and Lando (2001), Collin-Dufresne, Goldstein, and Helwege (2003), Cetin (2004), and Jarrow and Protter (2004) point out an intrinsic connection between these two approaches. Reduced-form models can be viewed as structural models analyzed under different information filtrations: Structural models are based on the information set available to the firm's management, which includes continuous-time observations of both the firm's asset value and liabilities; reduced-form models are based on the information set available to the market, typically including only partial observations of both the firm's asset value and liabilities.

4.2.2 The Black-Scholes-Merton Model

For the Black-Scholes-Merton model, based on Black and Scholes [1973] and Merton [1974], may think of equity and debt as derivatives with respect to the total market value of the firm, and priced accordingly. In the literature, considerable attention has been paid to market imperfections and to control that may be exercised by holders of equity and debt, as well as managers. With these market imperfections, the theory becomes more complex and less like a derivative valuation model.

With the classic Black-Scholes-Merton model of corporate debt and equity valuation, one supposes that the firm's future cash flows have a total market value at time t given by A_t , where A is a geometric Brownian motion, satisfying for constants μ and $\sigma > 0$, and where we have taken $d = 1$ as the dimension of the underlying Brownian motion B . One sometimes refers to A_t as the assets of the firm. We will suppose for simplicity that the firm produces no cash flows before a given time T . In order to justify this valuation of the firm, one could assume there are other securities available for trade that create the effect of complete markets, namely that, within the technical limitations of the theory, any future cash flows can be generated as the dividends of a trading strategy with respect to the available securities. There is then a unique price at which those cash flows would trade without allowing an arbitrage.

Original owners of the firm have chosen a capital structure consisting of pure equity and of debt in the form of a single zero-coupon bond maturing at time T , of face value L . In the event that the total value A_T of the firm at maturity is less than the contractual payment L due on the debt, the firm defaults, giving its future cash flows, worth A_T , to debtholders. That is, debtholders receive $\min(L, A_T)$ at T . Equityholders receive the residual $\max(A_T - L, 0)$. Suppose for simplicity that there are no other distributions (such as dividends) to debt or equity.

Bond and equity investors have already paid the original owners of the firm for their respective securities. The absence of arbitrage implies that at any time $t < T$, the total of the market values S_t of equity and Y_t of debt must be the market value A_t of the assets. This is one of the main points made by Modigliani and Miller [1958], in their demonstration of the irrelevance of capital structure in perfect markets.

4.2.3 Duffie And Lando Model

Duffie and Lando (2001) consider a model in which the default time is fixed by the firm's managers so as to maximize the value of equity. Investors cannot observe the assets directly, and receive only periodic and imperfect accounting reports. Assuming a given Markov process, A_t , where A_t represents the firm's value at time t , Duffie and Lando "obscure" the process A so that it can be observed only at discrete time intervals, and add independent noise. A discrete time process $Z_t = A_t + Y_t$ is obtained, where Y_t is the added noise, and which is observed at times t_i for $i = 1, \dots, \infty$.

Duffie and Lando were first to uncover the intrinsic connection between structural and reduced-form models of credit risk. They consider the structural model with endogenously determined default barrier and postulated that investors observe noisy and delayed accounting reports.

Since the key financial parameters are imperfectly observed, the firm's default incident is fundamentally unpredictable, conditional on the information available to the market observer. The new methodology based on the notion of incomplete information provides the link between structural ("microscopic") and reduced-form ("macroscopic")

models of credit risk and allows for derivation of the hazard rate, which involves certain basic assumptions regarding the cause of default risk.

The stopping time, τ , is therefore inaccessible. The default time τ is transformed from a predictable stopping time into an inaccessible stopping time since it is unclear how the asset value evolves between the time of the observations of the asset value. Default could occur unexpectedly prior to the next observation. Under these circumstances, the structural model becomes a reduced-form model by obscuring and reducing the information.

4.2.4 Giesecke Model

Giesecke (2005) deals with the case of a structural model in which investors have complete information about the asset value but incomplete information about the default threshold. Although constant, the default threshold is not known by the investors, who are forced to work under a distribution function for the default threshold. The impossibility of observing the default threshold makes the default time an unpredictable event. In this case, investors calculate the pricing trend in terms of the distribution function for the threshold and the observable historical asset value.

Giesecke also studies the cases of incomplete information for both the asset value and the default threshold. In contrast with the previous case in which investors have incomplete information about the default threshold but complete information about the asset value process, this case with imperfect information about the pricing trend calculated in terms of the threshold distribution and the distribution of the minimum historical asset level the pricing trend, calculated in terms of the threshold distribution and the distribution for the minimum historical asset level admits an intensity representation.

4.2.5 Giesecke And Goldberg Model

Giesecke and Goldberg (2004) consider the case in which the default barrier is random and unobserved—modeled as an horizontal line of the form $y = L$, where L itself is unknown and random. Since this random curve is independent of the underlying structural model, the default time τ is inaccessible. Given that the true level of liabilities is not disclosed to the public, investors use a priory distribution for the default threshold. Giesecke (2004) takes the incomplete information assumption in structural model one step further to model the default correlation. He provides a structural model in which the firms' default probabilities are linked via a joint distribution to their default

Investors do not have perfect information about either such thresholds or their joint distribution. However, they form a prior distribution which is updated when one such thresholds is revealed, which only happens when one of the firms defaults. In Giesecke (2004), investors have incomplete information about the firms' default thresholds but complete information about their asset processes. Giesecke and Goldberg (2004) extend this framework to one in which investors do not have information about either the firms' asset values or their default thresholds. In this case, default correlation is introduced through correlated asset processes, and, again, investors receive information about the firms' asset and default barrier only when they default. Such information is used to update their priors about the distribution of the remaining firms' asset values.

4.2.6 Çetin, Jarrow, Protter, And Yıldırım Model

Çetin, Jarrow, Protter, and Yıldırım (2004) depart from a structural model—as in Duffie and Lando—where the modeler's filtration, (F_t) , is a strict subfiltration of that variable to the firm's managers—investors receive only a reduced version of the information that firm's managers have. The authors claim that the default time is a predictable event for firm's managers, since they have enough information about the firm's fundamentals. But investors do not have access to such information.

Instead, investors observe a reduced version of this information. In the model, the firm's cash flow (L) is the variable that triggers default, after reaching some minimum levels during a given period of time.

Firm's managers can see levels, but investors only receive information about the sign of the L , making the default time an unpredictable event from their perspective. In this setting, investors derive the default intensity as seen by the market. The relevant barrier is now $L_t = 0$, for all $t \geq 0$, the cash flows. Investors only observe whether the cash flow is positive, zero or negative, and assume that the default time is the first time that the cash flows fall below zero, or when the cash flow both remains below zero for a certain period of time, and then doubles in absolute magnitude.

4.2.7 Jarrow, Turnbull, And Others Models

A class of reduced-form models that separates bankruptcy and the firm's underlying assets has attracted a lot of attention. These models rely on an approach suggested by Jarrow and Turnbull (1995, 1992) to price derivatives. The basic idea of this approach is to assume the presence of two exogenous stochastic term-structures—one risk-free and the other one that would be a credit spread over the first one—and bankruptcy that is an exogenous process, independent of the firm's underlying assets.

The combined term-structure is then used to price instruments under the absence of arbitrage opportunities and using martingale technology (Harrison and Kreps (1979) and Harrison and Pliska (1981)). This approach does not require estimates for the parameters of the firm's unobservable asset value, a common problem in the structural models, or a payoff priority structure of the firm's liabilities.

By way of extension of this approach, Jarrow, Lando and Turnbull (1997) specify the bankruptcy process as a discrete Markov chain, whose parameters are easily estimated using observable data.

Duffie and Singleton (1999) parameterize the losses at default as a reduction of the market value of defaultable securities observed at default, and show that these securities can be priced using a default-adjusted, risk-free rate process.

They show that the price of the securities using their framework accounts for both the probability and timing of default, as well as the effect of losses on default. Guo, Jarrow and Zeng (2005) model the recovery rate process within a reduced-form model using the firm's balance sheet structure. Wong and Wong (2007) develop a regime-switching model over the entire yield curve to examine the changes in default probabilities across different credit ratings.

4.3 ALTERNATIVE FORM CREDIT MODELS

These models go back to Artzner & Delbaen (1995), Jarrow & Turnbull (1995) and Duffie & Singleton (1999). Here we assume that default occurs without warning at an exogenous default rate, or intensity. The dynamics of the intensity are specified under the pricing probability. Instead of asking why the firm defaults, the intensity model is calibrated from market prices. The reduced form approach is not based on a model definition of default.

The dynamics of default are prescribed exogenously, directly under a pricing probability Q . The problem can be cast in the framework of point processes. Taking as given the random default time τ , define the default process by

$$N_t = 1_{\{\tau \leq t\}} = \begin{cases} 1 & \text{if } \tau \leq t \\ 0 & \text{if else.} \end{cases} \quad (4.1)$$

This is a point process with one jump of size one at default. Since the default process is increasing, it has an upward trend: the conditional probability at time t that the firm defaults by time s , $t \leq s$ is at least as big as N_t itself.

A process with this property is called a submartingale. A process with zero trend is called a martingale. This is a "fair" process in the sense that the expected gain or loss is zero.

The Doob-Meyer decomposition theorem enables us to isolate the upward trend from N . This fundamental result states that there exists an increasing process A_{∂} starting at zero such that $N - A_{\partial}$ becomes a martingale, see Dellacherie & Meyer (1982). The unique process A_{∂} counteracts the upward trend in N ; it is therefore often called compensator.

Interestingly, the analytic properties of the compensator correspond to the probabilistic properties of default. For example, the compensator is continuous if and only if the default time ∂ is unpredictable.

The default comes without warning; a sequence of announcing pre-default times does not exist. This is a desirable model property since it allows us to fit the model to market credit spreads. The compensator describes the cumulative, conditional likelihood of default. In the reduced form approach to credit, the compensator is parameterized through a non-negative process λ by setting

$$A_t^{\tau} = \int_0^{\min(t, \tau)} \lambda_s ds = \int_0^t \lambda_s 1_{\{\tau > s\}} ds. \tag{4.2}$$

With this assumption, λ_t describes the conditional default rate, or intensity: for small Δt and $t < \partial$, the product $\lambda_t \Delta t$ approximates the pricing probability that default occurs in the interval $(t; t + \Delta t]$. Any given non-negative process λ can be used to parameterize the dynamics of default.

4.3.1 Credit Migration Matrice Models

The rating scales is replaced by an equivalent numerical scale, i.e.

$$\{AAA, AA, A, BBB, \dots, 'default'\} \leftrightarrow \{1, 2, 3, 4, \dots, K\}. \quad (4.3)$$

The migration matrix then describes all possible transition probabilities given a rating scale

$$\mathbf{P}(t) = \begin{pmatrix} p_{1,1} & p_{1,2} & \dots & p_{1,K} \\ p_{2,1} & p_{2,2} & \dots & p_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ p_{K-1,1} & p_{K-1,2} & \dots & p_{K-1,K} \\ 0 & 0 & \dots & 1 \end{pmatrix}, \quad (4.4)$$

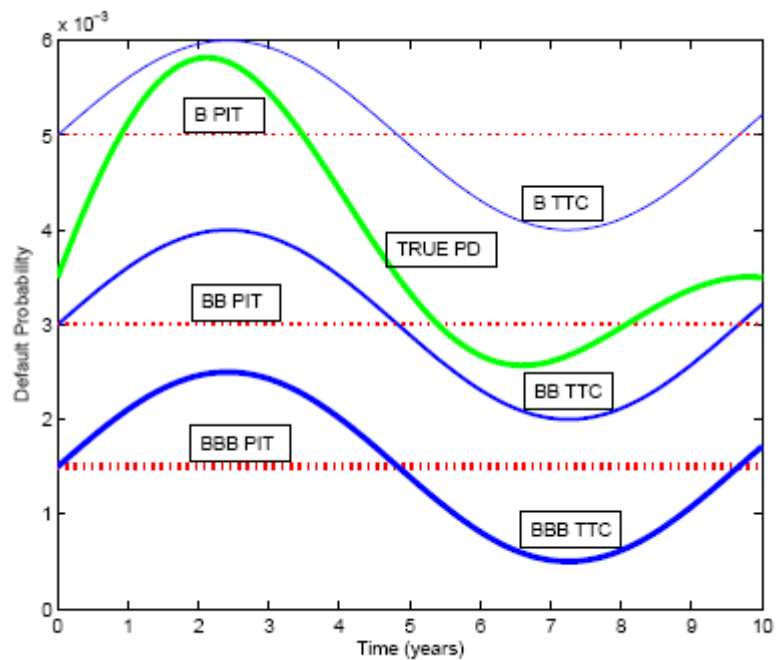
where each $p_{i;j}$ in (1) represents the transition probability from state i to state j if $i \neq j$ in a time period t . The rows represent the current rating of the obligors whereas the columns represent the future rating.

The last row K represents the absorbing state of default, the probability of leaving the default state equals zero. With the highest rating in row one, the elements below the diagonal are the probabilities for upgrades, and the elements above the diagonal are the probabilities for downgrades. The upper part of the matrix also includes the K th column which gives the default probabilities for the different ratings.

The diagonal elements represent the probabilities for the ratings to be preserved in period t . A major task is to describe the dynamics of the migration matrix as an underlying value.

The dynamics of this matrix depends on several factors. The first one which consider is the rating approach used as an input, i.e. what are the effects on the matrix entries if one uses a PIT or a TTC methodology, respectively.

Table no: 4.2 The Dynamics Of The Migration Matrix Model



**Source: Credit Migration Risk Modelling Andreas Anderssony and Paolo Vaniniz
June 9, 2009 Current draft: 06/2009**

4.3.2 The Affine Markov Chain Model

Hurd and Kuznetsov (2006) define the Affine Markov Chain model as follows. They consider a finite state space $\{1; 2... Kg\}$ where each state represents different rating classes via the mapping:

$$\{1, 2, 3, 4, \dots, K\} \leftrightarrow \{AAA, AA, A, BBB, \dots, 'default'\}. \quad (4.5)$$

The continuous time migration matrix through is defined as:

$$\mathbf{P}(t) = e^{\tau t \mathcal{L}}, \quad (4.6)$$

In the Affine Markov Chain model the rating for a firm is given by the value of the credit migration process $Y_t \in \{1; 2; \dots; K\}$, specified as a finite state Markov Chain in real time.

Hence the value of the process, Y_t gives the credit rating of a firm at time, t . If use the dynamics of the stochastic time change under the risk neutral probability measure,

the migration probability from rating i to rating j under Q equals:

$$Q(Y_t = j | Y_0 = i) = \mathbb{E}^Q \left[(\mathbf{P}(t))_{i,j} \right] = \mathbb{E}^Q \left[(e^{\tau t \mathcal{L}})_{i,j} \right] \quad \text{for } i, j = 1, 2, \dots, K. \quad (4.7)$$

4.3.3 The Generator Matrix Model

The Affine Markov Chain model specifies the generator as a static matrix. Once have estimated the generator, the only way to make the migration matrix time-inhomogeneous is via the stochastic time change. A static generator will have a constant rating direction.

Suppose that estimation the generator only once. Then the generator has to preformll on average and can be applied for several years. Following Israel, Rosenthal and i (2001) an average generator using migration data from Standard & Poor's collected over the last 25 years.

This generator produces the historical average migration matrix. This average matrix is characterized with a dominant diagonal, i.e. the probability for obligors to preserve their rating is larger then 50 percent, and an small negative direction, i.e. on average obligors migrate to lor grades than to upper grades. Hovewer, there is only this pessimistic view on obligors creditworthiness: There is no possibility to model an optimistic view at the same time.

Andersson (2007) shows that the existence of a static generator can not be confirmed for one out of ten years using Standard & Poor's yearly migration matrices. For PIT migration matrices there exists no generator for two out of three years.

This contrasts with the observation that in the academic literature existence of a true generator is in general assumed, Lando (1998), Arvanitis et al. (1999) and Hurd and Kuznetsov (2006, 2006). There are several ways to improve the static modelling approach. First, one could model a truly dynamic generator. Second, the Markov chain can be made time inhomogeneous using a time change which interacts with the static generator. Hurd and Kuznetsov (2006) use a static generator and obtain the non-homogeneity through a stochastic time change.

They also make it possible to include one or several extra generators in their model. The addition of further generators will however only have the effect that default probabilities will increase further. Bluhm and Overbeck (2007) show that there several inconsistencies between the above model prediction and empirical observations.

They introduce a nonhomogeneous generator instead of the static time-homogeneous generator. Lando and Sködeberg (2002) propose a dynamic generator, where every element in the generator is a stochastic process. However, the complexity of the model makes it difficult to obtain tractable solutions for credit derivatives pricing. Frydman and Schuermann (2007) propose a Markov mixture model to overcome the problem with time-homogeneity.

They use a mixture of two static generators which leads to a non-homogeneous generator. note that all models above are not able to take the negative direction into account. A change of direction is not possible. There are two further shortcomings which makes it necessary to enlarge the typical Affine Markov Chain approach of Hurd and Kuznetsov (2006a). First, their model focuses too heavily on the Probabilities of Default (PD), neglecting the transition states of the migration matrix. This implies that over longer time horizons, i.e. three to five years, the model gives unrealistic probabilities for non-default migrations compared to true probabilities.

However, the model still provides accurate PD. More precisely, for a period of economic downturn observe increased PD and higher probability for upgrades for all rating classes in their model. This model output is not in line with empirical observations and has its origin in the static generator.

Second, using a Affine Markov Chain model only non-decreasing PD term structures arise. The model has no ability to create inverted PD curves since the time change can only stretch or bend the term structure curves but not change the sign of their slope. But if an obligor overcomes a financial distress, the default probability will decrease over the years, i.e. inversion of the term structure is a ll-known empirical observation.

In an Affine Markov Chain model have to either let the model follow the default probability at the beginning of the period and by that overestimate the future default probability, or must underestimate the short term default probability to allow for an convergence of the long term default probability.

Both cases affect the price of any long term Credit Derivative, leading to misspricing and arbitrage opportunities. Bluhm and Overbeck (2007) highlight these shortcomings concerning PD term structure when it comes to non-decreasing PD curves. However, they do not discuss inverted or other exotic PD curves.

The model is able to account for changes in both rating speed and rating direction (get a possibility to consider different economic scenarios) and which maintains the analytical tractability of the Affine Markov Chain approach. The model propose is a Regime Shifting Markov Mixture model.

4.3.4 The Multi-State Latent Factor Intensity Model

The multi-state latent factor intensity (MLFI) model is a multi-state generalization for multivariate point processes of the latent factor intensity (LFI) model of Bauns and Hautsch (2003). Consider a set of K units (or firms) whose event-histories can be adequately described by the history of transitions between a finite set of states. The states in empirical application will be the set of credit ratings for issuers as assigned by Standard and Poor's (S&P).

The data set has a clear panel structure and consists of the exact dates and the corresponding type of the rating changes recorded for each firm in the sample. In order to account for unobserved dependence between the transition histories in a parsimonious way, introduce a common factor. This assumption is standard in the credit risk literature and is used to prevent the model's corresponding joint state-space becoming quickly unmanageable due to its size.

Gagliardini and Gourieroux (2004) provide a short discussion of this curse of dimensionality problem. For example, in the case of three rating classes (AAA, AA,A), $s = 1$ denotes a downgrade from AAA to AA, $s = 2$ from AAA to A, $s = 3$ an upgrade from AA to AAA, up to $s = S = 6$ an upgrade from A to AA. Next, define the right-continuous counting processes $N_k(t)$ and $N(t)$. The process $N(t)$ makes a jump of unit size at each time there is a rating event for one of the K units. Similarly, $N_k(t)$ jumps at the times there is a credit event for unit k such that:

$$N(t) = \sum_{k=1}^K N_k(t). \quad (4.8)$$

These point processes are marked because at each event time also observe the transition type of the unit, i.e., the specific type of upgrade or downgrade. In fact, the counting process $N_k(t)$ can be expressed as the sum of S counting processes $N_{sk}(t)$ that keep track of the total number of transitions of type s for firm k .

$$N_k(t) = \sum_{s=1}^S N_{sk}(t), \quad N(t) = \sum_{k=1}^K N_k(t) = \sum_{s=1}^S \sum_{k=1}^K N_{sk}(t). \quad (4.9)$$

4.3.5 Default-At-Maturity And First-Passage Time Models

Two main approaches are in use for modeling the default risk of a single issuer: the intensity-based or reduced-form and structural approaches. The reduced-form approach assumes that the timing of default depends on an exogenous stochastic process, and the default event is not linked to any observable characteristic of the firm.

In contrast, the structural approach, which traces its roots to Black and Scholes (1973) and Merton (1974), starts with the observation that default occurs when a firm is unable to continue servicing its debt, say, because of economic reasons related to the business cycle.

Under absolute priority rules, equity shareholders are residual claimants on the assets of the firm since bondholders are paid first in case of default. Equity shareholders, in effect, hold a call option on the assets of the firm, with a strike price equal to the debt owed to bondholders.

Similarly, the value of the debt owed by the firm is equivalent to a default-free bond plus a short position on a put option on the assets of the firm.

Structural models rely on the conceptual insight that default occurs when the asset value of the firm is less than what the firm owes to its debtors.

However, these models differ with respect to their assumptions regarding the timing of default. In the model of Merton (1974) as in other structural models, for a firm that issues a zero-coupon bond, default occurs at maturity since this is the only period in which creditors can verify the asset value of the firm.

These are examples of default-at-maturity models. In other structural models, default occurs when the asset value of the firm, V , falls below the value of the liabilities of the firm, L , at some default time τ .

The problem of default, in mathematical language, is equivalent to a first passage time problem, also known as a first stopping or exit time problem.

First passage time models include, among others, those of Kim, Ramaswamy, and Sundaresan (1993), Nielsen, Saá-Requejo, and Santa-Clara (1993), Longstaff and Schwartz (1995) and Saá-Requejo and Santa Clara (1999) More recently, Capuano (2008) has proposed a non-parametric structural model to estimate the probability of default.

This model estimates the probability of default implied by equity options by calibrating the probability density function of the value of the assets using the market prices of option contracts. Such a model makes it possible to estimate the default barrier within the model, while capturing deviations from log-normality.

The model has performed well in the context of the global financial crisis, providing early warning signals of distress for some key financial institutions.

4.3.6 Portfolio Credit Risk Models

Knowledge of the probability of default of individual firms opens the way to use portfolio credit risk models to assess the probability that a subset of the firms in a sample default during a pre-specified period of time. Put differently, if there is information about losses given default associated with securities issued by each single issuing firms, it is possible to estimate the loss distribution of a portfolio that holds these securities.

Assessing the probability of default among a subset of firms requires computing the distribution of the number of defaults. The multi-factor normal Gaussian copula, which was introduced by Vasicek (1987) and extended by Li (2000), is the workhorse structural model for such a computation. In the Gaussian copula, the normalized asset value of firm i , x_i , depends on a single common factor, M , and an idiosyncratic shock.

$$x_i = a_i M + \sqrt{1 - a_i^2} Z_i, \quad (4.10)$$

where x_i , M , and Z_i are standard normally distributed variables. The coefficient a_i , or factor loading, is restricted to values between 0 and 1 and measures the dependence of the asset value on the common factor.

4.3.7 Vendor Credit Portfolio Risk Models

There are four main vendor credit portfolio models that have been widely implemented by commercial banks. These models are used to assess banks credit risk and as input for calculating required regulatory capital standards set down in the Internal Ratings-based Approach (IRB) introduced by the Basel II Capital Accord. While the various approaches the outputs of these models typically include a probability of default or a loss distribution for a given default horizon (one year in most cases).

One model is structural and based on option pricing theory. This approach builds on the asset valuation model originally proposed by Merton (1974) and is commercially distributed as Moody's KMV's Credit Monitor. It is known as a structural model of default as it is based on modelling a firms value and capital structure. It links default events to the firm's economic fundamentals (equity and assets).

Table no: 4.3 Corporate Bond's Average Cumulative Default Rates

**Moody's corporate bond
average cumulative default
rates (%)**

Years	1	2	3	4	5
Aaa	0.00	0.00	0.00	0.07	0.23
Aa1	0.00	0.00	0.00	0.31	0.31
Aa2	0.00	0.00	0.09	0.29	0.65
Aa3	0.09	0.15	0.27	0.42	0.60
A1	0.00	0.04	0.49	0.79	1.01
A2	0.00	0.04	0.21	0.57	0.88
A3	0.00	0.20	0.37	0.52	0.61
Baa1	0.06	0.39	0.79	1.17	1.53
Baa2	0.06	0.26	0.35	1.07	1.70
Baa3	0.45	1.06	1.80	2.87	3.69
Ba1	0.85	2.68	4.46	7.03	9.52
Ba2	0.73	3.37	6.47	9.43	12.28
Ba3	3.12	8.09	13.49	18.55	23.15
B1	4.50	10.90	17.33	23.44	29.05
B2	8.75	15.18	22.10	27.95	31.86
B3	13.49	21.86	27.84	32.08	36.10

*Source: Carty & Lieberman [96a]
— Moody's Investors Service*

Source: CreditMetrics™—Technical Document Copyright © 1997 J.P. Morgan & Co. Incorporated

The next group of models are reduced form models as these do not model firms, assets or capital structure. These models specify that credit events occur owing to some type of exogenous statistical process. Reduced form models can be divided into models that construct credit events as migrations between rating classes (including default) known as credit migration models; and those that specify the default time known as intensity models.

The credit migration approach has been developed by JP Morgan and is commercially implemented as CreditMetrics. This methodology is based on the probability of moving from one credit quality to another, including default, within a given time horizon. It is based on an ordered probit model, and uses Monte Carlo simulation to create a portfolio loss distribution on the horizon date. Another way of quantifying credit risk is the CreditPortfolioView model developed by McKinsey, which uses a discrete time multi-period model in which default probabilities are conditional on the macro variables such as unemployment, the level of interest rates and economic growth all of which, to a large extent, influence the credit cycle in the economy.

Finally, CreditRisk+ (CR+) by Credit Suisse Financial Products (CSFP) uses an actuarial approach, and focuses purely on default. In this model, de-fault rates are not in absolute levels such as 0.25 percent for a BBB-rated issuer. But are treated as continuous random variables. Given that most banks have large numbers of borrowers, some of these borrowers default probabilities may be correlated.

Moreover, since borrowers may be concentrated in certain economic sectors, it makes sense for a bank to take these factors into account when assessing the overall level of credit risk or potential losses in its loan portfolio. In the CR+ model, the default correlations are not modelled with indicators for regional economic strength or industry-specific weakness but by estimates of the volatility of the default rate.

These estimates are produced by using the standard deviation of the default rate and are designed to depict the uncertainty that observed default rates for credit ratings vary over time. This feature allows a better capturing of the effect of default correlations and of the long tail in the portfolio loss distribution given that default correlations induced by external factors are difficult to observe and may be unstable over time.

The model allows exposures to be allocated to industrial or geographical sectors as well over varying default horizons. As inputs, data similar to those required by Basel II are used. The main advantage of the CR+ model is that it requires a relatively limited amount of data an important consideration when using publicly available information.

To sum up, each group of models has both advantages and disadvantages and successful implementation depends on the specific purpose. Given that the aim of this paper is to generate a proxy of overall credit risk for a sample of EU LCBGs, structural models based on their public exposure data such as Moody's KMV's default model, cannot readily be applied to some of these sectors (the household sector) in order to calculate default probabilities, as data on equity prices or asset volatilities are not available for this sector.

4.4 STRUCTURAL MODEL OUTPUT

Credit risk is the distribution of financial losses due to unexpected changes in the credit quality of a counterparty in a financial agreement. Examples range from agency downgrades to failure to service debt to liquidation. Credit risk pervades virtually all financial transactions. The distribution of credit losses is complex. At its center is the probability of default, by which mean any type of failure to honor a financial agreement. To estimate the probability of default, need to specify

- i) a model of investor uncertainty;
- ii) a model of the available information and its evolution over time; and
- iii) a model definition of the default event.

However, default probabilities alone are not sufficient to price credit sensitive securities. need, in addition,

- a) a model for the riskfree interest rate;
- b) a model of recovery upon default; and
- c) a model of the premium investors require as compensation for bearing systematic credit risk.

There are two primary types of models that attempt to describe default processes in the credit risk literature: structural and reduced form models. Structural models use the evolution of firms' structural variables, such as asset and debt values, to determine the time of default. Merton's model (1974) was the first modern model of default and is considered the first structural model.

In Merton's model, a firm defaults if, at the time of servicing the debt, its assets are below its outstanding debt. A second approach, within the structural framework, was introduced by Black and Cox (1976). In this approach defaults occur as soon as firm's asset value falls below a certain threshold.

The structural literature on credit risk starts with the paper by Merton (1974), who applies the option pricing theory developed by Black and Scholes (1973) to the modelling of a firm's debt. In Merton's model, the firm's capital structure is assumed to be composed by equity and a zero-coupon bond with maturity T and face value.

The paper by Black and Cox (1976) is the first of the so-called First Passage Models (FPM). First passage models specify default as the first time the firm's asset value hits a barrier, allowing default to take place at any time. When the default barrier is exogenously fixed, as in Black and Cox (1976) and Longstaff and Schwartz (1995), it acts as a safety covenant to protect bondholders. Alternatively it can be endogenously fixed as a result of the stockholders' attempt to choose the default threshold which maximizes the value of the firm (Leland 1994 and Leland and Toft 1996.)

Credit pricing models changed forever with the insights of Black and Scholes (1973) and Metron (1974). Jones, Mason and Rosenfeld (1984) punctured the promise of these "structural" models of default by showing how these types of models systematically underestimated observed spreads.

Their research reflected a sample of firms with simple capital structures observed during the period 1977 to 1981. Ogden (1987) confirmed this result finding that the Merton model under-predicted spreads over U.S. treasuries by an average of 104 basis points.

KMV (now Moody's KMV or MKMV) revived the practical applicability of structural models by implementing a modified structural model called the Vasicek-Kealhofer (VK) model (see Crosbie and Bohn (2003), Kealhofer (2003a), Kealhofer (2003), and Vasicek (1984)). This VK model is combined with an empirical distribution of distance to-default to generate the commercially available Expected Default Frequency, or EDF credit measure.

The VK model builds on insights gleaned from modifications to the classical structural model suggested by other researchers. Black and Cox (1976) model the default-point as an absorbing barrier. Geske (1977) treats the liability claims as compound options. In this framework, Geske assumes the firm has the option to issue new equity to service debt. Longsta and Schwartz (1995) introduce stochastic interest rates into the structural model framework to create a two-factor specification.

Leland and Toft (1996) consider the impact of bankruptcy costs and taxes on the structural model output. In their framework, they assume the firm issues a constant amount of debt continuously with fixed maturity and continuous coupon payments. Collin-Dufresne and Goldstein (2001) extend the Longsta and Schwartz model by introducing a stationary leverage ratio, allowing firms to deviate from their target leverage ratio in the short run, only.

While empirical evidence is still scant, a few empirical researchers have begun to test these model extensions. Lyden and Saraniti (2000) compare the Merton and the Longsta-Schwartz models and find that both models under-predicted spreads; the assumption of stochastic interest rates did not seem to change the qualitative nature of the finding. Eom, Helge, and Huang (2003) find evidence contradicting conventional wisdom on the bias of structural model spreads.

This model appears to produce unbiased, robust predictions of corporate bond credit spreads. (see Bohn (2000) and Agrawal, Arora, and Bohn (2004) for more details.) Some important modifications to the typical structural framework include estimation of an implicit corporate-risk-free reference curve instead of using the U.S. treasury curve.

Some of the under-prediction found in the standard testing of the Merton model likely results from choosing the wrong benchmark curve in the sense that the spread over U.S. treasuries includes more than compensation for just corporate credit-risk.

The choice of credit default swap data for testing ensures a neutral ground on which the success of the different models can be evaluated. None of the models are calibrated on the data used for testing. This testing strategy enables us to avoid the pitfalls of testing models on data similar to the data used to estimate the models. The structural models are estimated with equity data and the reduced-form model is estimated with bond data.

All these modifications contribute to producing a more usable structural model. The structural model is particularly useful for practitioners in the credit portfolio and credit risk management fields. The intuitive economic interpretation of the model facilitates consistent discussion regarding a variety of credit risk exposures. Corporate transaction analysis is also possible with the structural model.

If an analyst wants to understand the impact on credit quality of increased borrowing, share repurchases, or the acquisition of another firm, the structural model naturally lends itself to understanding the transaction's implications. In general, the ability to diagnose the input and output of the structural model in terms of understandable economic variables (e.g. asset volatility as a proxy for business risk, the market's assessment of an enterprise's value, and the market leverage) facilitates better communication among loan originators, credit analysts, and credit portfolio managers.

They find structural models that depart from the Merton framework tend to over-predict spreads for the debt of firms with high volatility or high leverage. For safer bonds, these models, with the exception of Leland-Toft, under-predict spreads. On the commercial side MKMV offers a version of the VK model applied to valuing corporate securities, which is built on a specification of the default-risk-free rate, the market risk premium, liquidity premium, and expected recovery in the context of a structural model.

The VK model framework is used to produce default probabilities defined as EDF credit measures and then extended to produce a full characterization of the value of a credit risky security. The recent availability of credit default swap data provides a new opportunity to understand the pros of both the structural and reduced-form modeling frameworks.

4.5 MODELS CALIBRATION

Calibration is the process of assigning the parameters of the model such that the model reproduces market prices. One set of market prices is the term structure of credit spreads (or default probabilities).

Further market prices, such as prices of default swaptions, provided they are available and liquid, may be suitable for calibrating the dynamics. In the absence of a liquid market for such claims, calibrating the dynamics via historical data may be a feasible alternative.

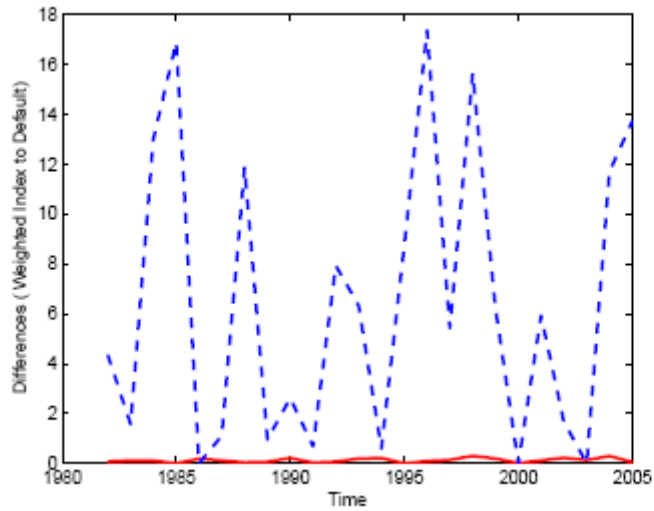
It is also the case that calibration to a given term structure imposes some restrictions on the dynamics parameters – in other words, given a set of dynamics parameters, it is not possible to achieve satisfactory calibration to an arbitrary term structure.

The allocation of the parameters to spot curve calibration and dynamics calibration is justified as follows: in a model with a jump intensity of zero, the resulting time-change process is deterministic, which corresponds to the Overbeck-Schmidt model.

In this case, the only parameters that are relevant for calibration to a given spot curve are the initial variance and the deterministic function and the dynamics are fixed by the deterministic time-change. Only when the jump intensity is greater than zero do the dynamics change, in which case all parameters allocated to the dynamics calibration become relevant for the dynamics.

Numerically by minimising the error between market-given and model computed default probabilities.

Table no: 4.4 Weighted Index To Default



Source: Migration Risk Modelling Andreas Andersson and Paolo Vanini June 9, 2009 Current draft: 06/2009

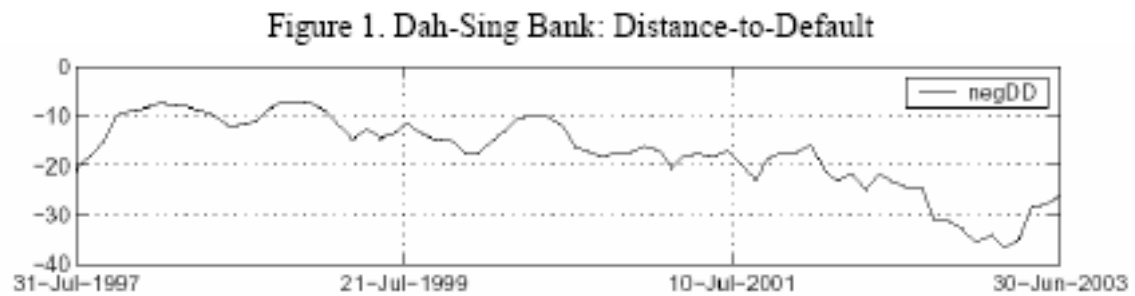
4.5.1 Distance To Default

Structural models rely on the concept of distance-to-default. This concept is a standardized measure of the difference between the firms' asset and liability values, which, theoretically, depends on the option-like features of the equity value of a firm. Such features are derived from an elementary accounting identity whereby the value of the firm, V (or the value of its assets), is equal to the sum of the values of its debt, D , and equity, E . Because debt is senior to equity, shareholders are residual claimants on the firm: the firm's assets are first used to pay debt holders in case of default, and whatever is left is distributed to shareholders. Concisely, the value of equity can be written as ;

$$E = \max(0, V - D) \quad (4.13)$$

The payoff to equity holders is equivalent to a call option on the value of the firm with a strike price equal to the face value of debt. The strike price is also known as the default barrier. Given an option pricing formula, knowledge of any two of the following three variables—the value of the firm, the debt od by the firm, and the market value of equity is sufficient for estimating the remaining unknown variable.

Table no: 4.5 Recent Advances in Credit Risk Modeling



Source: IMF Working Paper Monetary and Capital Markets Department Recent Advances in Credit Risk Modeling

The Black-Scholes-Merton option pricing formula for European call options is the basis for most practical applications. The strike price is set equal to the level of the firm's short-term liabilities and half its long-term liabilities. For the Merton (1974) model, the distance-to-default T periods ahead, DD_T , is given by

$$DD_T = \frac{\ln \frac{V}{D} + \left(\mu - \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}}, \quad (4.14)$$

4.5.2 Firm Heterogeneity - Diversification

To take full account of firm heterogeneity in credit risk places great demands on the data. When firms are public and have traded securities such as stocks, bonds, or even credit default swaps (CDS), as well as third party assessments such as public credit ratings, there is great scope for allowing and accounting for heterogeneity. But this scenario is limited to a small minority of firms; indeed most loans in banks' portfolios are to privately held firms about which (and the banks) know rather little. In that case one may be forced to settle for the credit portfolio solutions obtained under homogeneity.

To consider both observed and unobserved types of heterogeneity. The former is relatively easy to deal with and does not pose any particular technical difficulties.

The latter (unobserved heterogeneity) is more difficult and will be the focus of our analysis. Note that parameter heterogeneity refers to differences in population values of the parameters across different firms and prevails even in the absence of estimation uncertainty.

Vasicek and Gordy and examine the consequences of incorrectly neglecting the heterogeneity of return correlations and default thresholds across firms for the analysis of loss distributions. The default threshold captures a variety of firm characteristics such as balance sheet structure, including leverage, and intangibles like the quality of management.

This heterogeneity can be random — differences in factor loadings are purely random around a fixed mean — and/or the differences could be systematic — mean factor loadings could differ across industries but are randomly distributed around the industry mean, across firms within an industry.

Theoretical set-up is quite general and imposes few distributional and parametric restrictions. The theoretical results show a complex interaction between the sources of heterogeneity and the resulting loss distribution.

Find that neglecting heterogeneity in default thresholds and/or mean returns results in underestimation of expected losses, and its effect on portfolio risk is ambiguous.

This is a new result and arises due to the nonlinear nature of the relationships that prevail between the return process, the default threshold and the resultant default (and hence loss) process. Differences in asset values and default thresholds across firms do not disappear by cross-section averaging even if the differences across firms are random and the underlying portfolio is sufficiently large.

In comparing heterogeneous loss portfolios it is therefore important that appropriate adjustments are made so that the different portfolios all have the same ELs. In general this can be achieved by allowing for systematic heterogeneity across firms, e.g. by grouping firms into industries, regions, distances to default (e.g. credit rating), or a combination of those.

For the same level of EL, the impact of allowing for heterogeneity on the shape of the loss distribution is complex and depends on the source and degree of heterogeneity random differences in default thresholds result in lower risk, whether measured by UL or typical VaR levels (99 percent, 99.9 percent), so long as cross firm return correlations are homogeneous.

However, in the more general case where cross firm return correlations are also heterogeneous, the effects of heterogeneity on unexpected loss and VaR levels are ambiguous. The net effect of combining heterogeneity in both sources is hard to predict systematically, but our empirical application, designed to be typical and representative, shows risk to be reduced — both UL and VaR decline so that neglected heterogeneity results in overestimated risk. Therefore falsely imposing homogeneity could be quite costly.

But as the 2007 market turmoil in structured credit has revealed, mixing heterogeneous assets like subprime mortgage securities with investment grade bonds need not reduce risk, and investors that neglect such heterogeneity do so at their peril.

Along the way derive analytic solutions to loss distributions under parameter heterogeneity, assuming that the cross-section means and variance/covariances of the firm parameters are known; under homogeneity these variances and covariances are set to zero. Such derivations are important since they allow us to calibrate loss distributions for cases where there is little or no data to estimate the extent of parameter heterogeneity (which is practically the case for most of bank lending), using available estimates based on publicly traded securities.

The latter estimates are not perfect and will be subject to errors, but are likely to be more appropriate than setting the variance and covariances to zero. This result marks our second contribution to the literature.

Practical relevance for credit portfolio managers, especially when only limited data is available. The manager will likely have a reasonable grasp of average or expected loss of the portfolio, but might be less confident about the shape of the loss distribution.

Yet this shape is critical for risk assessment and is influenced significantly by the heterogeneity of the underlying portfolio. Its show how this heterogeneity can be easily parameterized and estimated for portfolios where data is plentiful and then applied to portfolios for which data is limited, as may be the case when the underlying assets are not publicly traded which is the case for the bulk of a bank's loan portfolio; one specific example may be the securitization of small business loans.

The importance of these theoretical insights are illustrated using a portfolio of about 600 publicly traded U.S. firms. Return regressions subject to different degrees of parameter heterogeneity are estimated recursively using six ten-year rolling estimation windows, and for each estimation window the loss distribution is then simulated out-of-sample over a one-year period. The predictions made by theory are confirmed in this application and are found to be robust across the six years.

Heterogeneity in the default threshold or probability of default (PD), measured for instance by a credit rating, is of first order importance in affecting the shape of the loss distribution: allowing for ratings heterogeneity alone results in a 20 percent drop in loss volatility (keeping EL's constant) and 40 percent drop in 99.9 percent VaR, the level to which the risk rights in the New Basel Accord are calibrated. Allowing for additional heterogeneity results in a further 10 percent drop in 99.9 percent VaR.

This result has important policy implications as a PD estimate through a credit rating, whether generated by a bank internally or provided by a rating agency externally, is the one parameter (of those considered here) that is allowed to vary in the New Basel Capital Accord.

To analyze the impact of neglected heterogeneity on credit risk, use a simple multifactor approach which is easily adapted to this task. Multifactor models have been used extensively in finance following Ross (1976) and Chamberlain and Rothschild (1983).

Their application to credit risk has been more recent. A notable example is its use in the CreditMetrics model as set out in Gupton, Finger and Bhatia (1997). Gordy (2000) and Schönbucher (2003,) provide useful reviews. A separate line of research has focused on correlated default intensities as in Lando (1998), Schönbucher (1998), Duffie and Singleton (1999), Duffie and Gârleanu (2001), Collin-Dufresne, Goldstein and Hugonnier (2004), and Duffie, Saita and Wang (2007); with a review by Duffie (2005).

There are also a host of other approaches, including correlated (but non-systematic) jumps at default (Driessen 2005, Jarrow, Lando, and Yu 2005), the contagion model of Davis and Lo (2001) as well as Giesecke and Bert's (2004) indirect dependence approach, where default correlation is introduced through local interaction of firms with their business partners as well as via global dependence on economic risk factors.

The Hull and White paper provides an illustration of the impact of correlation and ratings heterogeneity on an nth-to-default CDS. In short, the literature on modeling default dependence is growing rapidly along different paths, and there is as yet no consensus which approach is best. Our paper does not address that issue, but it does highlight, using a factor approach, the impact of neglected heterogeneity.

This issue of neglected heterogeneity clearly also arises in the case of other approaches that focus on correlated default intensities or copulas; leave that for others to explore. The factor structure considered here does allow us to explore two distinct channels of heterogeneity: one that is shared, namely factor sensitivities, and one which is specific to firms within a given grouping (e.g. credit rating), namely the default threshold or the distance to default.

Results have implications for risk and capital management as well as for pricing of credit assets. For example, in the case of a commercial bank, ignoring heterogeneity may result in underprovisioning for loan losses since EL is underestimated, and may result in overcapitalization against (bank) default since risk is overestimated. The risk assessment and pricing of complex credit assets such as collateralized debt obligations (CDO's) may be adversely affected since they are driven by the shape of the loss distribution which is then segmented into tranches. In particular, ignoring heterogeneity would result in excessive subordination for senior tranches as risk is overestimated.

4.5.3 Stochastic Filtering

Factor models are frequently employed in financial mathematics, since they lead to fairly parsimonious models. Stochastic filtering comes into play when these factors are observed only indirectly, possibly because they are hidden in additional noise.

There is a large body of more statistically focused work devoted to building credit quality estimation models, which seek to predict future default. One can identify three basic approaches to estimating default likelihood: qualitative dependent variable models, discriminant analysis, and neural networks.

All of these approaches are strictly quantitative and will at least yield a ranking of anticipated default likelihoods and often can be tuned to yield an estimate of default likelihood. Linear discriminant analysis applies a classification model to categorize which firms have defaulted versus which firms survived.

With a static generator, the stochastic time change is the only dynamic parameter in the Affine Markov Chain model. Given a constant negative direction created by the generator the time change speeds up during recessions and slows down during expansions. Since time can not run backwards, obtain the best state when the time change approaches zero for a period of real time. Hence the best state only preserves the current ratings. The stochastic time change can by its construction therefore only affect how fast obligors reach the default state.

In this approach, a historical sample is compiled of firms which defaulted with a matched sample of similar firms that did not default. Then, the statistical estimation approach is applied to identify which variables (and in which combination) can best classify firms into either group.

The best example of this approach is Edward Altman's Z-scores; first developed in 1968 and now offered commercially as Zeta Services Inc. This approach yields a continuous numerical score based on a linear function of the relevant firm variables, which – with additional processing – can be mapped to default likelihoods.

A simple way to understand the argument offered by Jarrow and Protter (2004) is to focus on the simple structural model of Merton (1974). If the asset value is observed continuously, the default event is predictable in the sense that it is possible to observe if the asset value is moving towards the default barrier (or the face value of the firm's liabilities). However, if the asset value re to be observed only in relatively long, discrete intervals of time, it would not be possible to know whether the firm is close to default in between intervals.

The academic literature is full of alternative techniques ranging from principal components analysis, self-organizing feature maps, logistic regression, probit/logit analysis and hierarchical classification models.

4.6 EMPIRICAL IMPLEMENTATION USING EUROPEAN DATA

Estimating portfolio credit risk models requires due to the fact that several EU banks were not reporting explicitly about the country of origin and the industry sector that an exposure relates to tried to approximate this information on the following basis.

For aggregate loan exposure figures in annual reports that had neither a specification towards the industry sector nor the country of origin or just one of these two dimensions missing assume a uniform distribution, split the exposures into the available entries for each dimension following the average percentage values that could be calculated from the available data.

A second necessary input for CreditRisk+ is probabilities of default and their volatilities for the various economic sectors. These re calculated based on data provided by Moody's KMV. Time series observations of default probabilities for households re not available. In this case, default probabilities re used based on previous work including work by the Basel Committee and on individual banks own estimates of probabilities of default for the household sector.

PDs for each of the 14 sectors re calculated as the median EDF value per time period and sector. There are further measures of default rates that could be included in the model. Instead of the Moody's KMV data one could think about using implied default probabilities extracted from CDS prices broken down by industry sectors (see Schneider, Sögner, and Veza (2007)). Since exposure data are generally not harmonised as each bank has its own definition of various types of lending, they re mapped to 14 economic sectors to make the data comparable with the Moody's KMV data.

Furthermore, our portfolio was expanded in order to make it more granular by assuming 80 percent of the portfolio was of standard credit quality, with the remaining 20 percent of the portfolio split equally between higher and lor credit quality segments.

The default probabilities of the lower and higher credit quality portions of the portfolio are also adjusted to respect the differing credit qualities. A granularity adjustment has already been proposed by the Basel Committee on Banking Supervision (2001). There are several theoretical approaches to do this.

Instead of an artificial increase of the number of exposures in our portfolio could as well first calculate the VaR and afterwards adjust this figure by a so called granularity add-on (Gordy (2003)). The latter is first estimated based on a theoretical model and then added to the ordinary VaR estimate.

There are several ways to include LGDs into the VaR estimation. First, initially considered exposure specific LGDs based on LGD values from LCBGs. LGDs based on the Basel II Capital Accord, and also took into account the experience of practitioners in commercial banks. As the majority of LGDs in this study can be classified as stressed or economic down turn LGDs, according to the fifth Basel II Quantitative Impact Study, the loss distributions for each bank's portfolio may be more extreme implying higher VaR estimates than those obtained using through-the-cycle LGDs.

However, publicly available data for LGDs on an industry and country specific level are still very limited, and better disclosure of LGD information would be a useful addition to what financial institutions already publish. In this paper, assume that LGDs stay constant over time and consequently are not influenced by sector or macroeconomic shocks (Avesani, Liu, Mirestean, and Salvati (2006)).

It can be seen that the exposures and LGDs vary, as do the probabilities of default for corporate and financial institutions sectors. Owing to a lack of data on households, their default probabilities remain constant. A further point to note is that the largest expected loss in this example. household consumer credit. comes from a relatively small exposure caused by a high LGD and a high default probability. Because of the lack of institution-specific LGD information, use stochastic LGD's as a robustness check for the VaR estimation. These are based on the following stochastic beta process.

$$y = f(x|\alpha, b) = \frac{1}{B(\alpha, b)} x^{\alpha-1} (1-x)^{b-1} I_{(0,1)}(x) \quad (4.15)$$

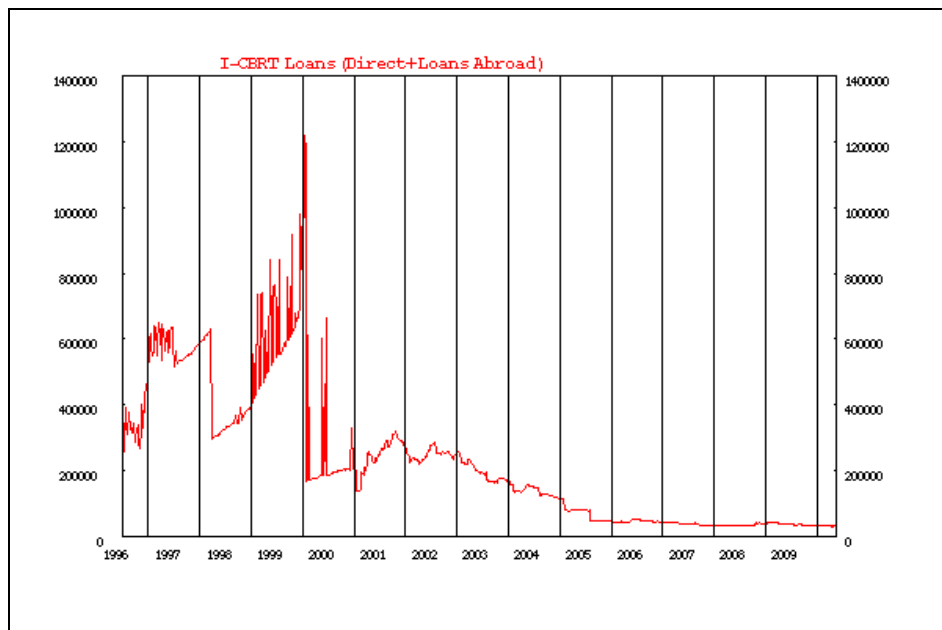
5.CREDIT RISK MODEL IN TURKISH BANKING SYSTEM

5.1 CREDIT RISK MANAGEMENT IN TURKISH BANKING SYSTEM

Turkish economy has very volatile performance as a result of domestic and external crises in recent years. After 2001 crises BRSA created a sustainable banking system in Turkey. Especially BRSA generated healthy operating environment and concentrated efficiency market condition in market. On the other hand sustainability problem caused from government huge budget deficit for many years.

These unprevented system giving a chance to the banks for generated income from treasury business work like as interest gains and operations benefits. These structure caused a unhealthy operating environment in along time (open position and operating margins). Efficiency problems of the system, large government-bond portfolios exposed to interest rate risk and uncontrollable budget increased abnormal size. In this period, Turkish banks liabilities that are significantly shorter than assets, and they were also exposed to exchange rate risk because of their short foreign currency positions.

Table no: 5.1 CBRT Loans Supervision



SOURCE: Central Bank of the Republic of Turkey (CBRT), BRSA)

Another important problem arising from the loan growth is the free capital level, which is an ongoing problem for the Turkish banking sector. In Turkey bank's investment-grade status depends almost entirely upon an expectation of government support, at the same time anticipated systemic support continues to argue for high relative deposit until 2001. These are the fundamental wrong for Turkish banking system. BRSA correalition caused in local or foreign currency terms become important ratings drivers, especially for banks in risk management department.

Banking head departments particularly challenging to assess relative default risk in this environment, they tried to balanced confidence sensitivity of the markets and the need for new establishment likes as international partnership. Koçbank – Unicredit, Denizbank – Dexia, TEB – Paribas to restore financial stability and stronger capital adenyency. Their risk management approaches changed day by day.

The biggest challenge for Turkish bank to setting rating levels for intrinsically weak form to strong form and finally gained investable market area. These development provided by 2 important issues. First one is parental support another one govermental support. Liquidity and capital constraints supported to subsidiaries for stable banking activities.

One party programme and fiscal and monetary policies efficiency caused a stable economic outlook for international investor and banks. Financial strenghs of the Turkish bank relevent by stronger risk management process and dynamic credit risk apporach. This dynamic and unique risk management approach efficiency based on valuable and defensible business franchises, strong financial fundamentals and a very predictable and stable operating environment.

The main goal of the credit management system is to set the rules of day -to-day credits department duties and determine the credit risk policy of banks.

The procedures of credits department are designed as a risk oriented document as most of the department's tasks are based on measuring, monitoring and managing risk. The risk that dealing with are credit risk - legal & integrity risk and operational risk.

As we remember again credit risk is the current or prospective risk to earnings and capital arising from an obligor's failure to meet the terms of any contract with the institutions or otherwise fail to perform as agreed , including the possibility of restrictions on or impediments to the transfer of payments from abroad.

Credit risk is found in all activities where profitability depends on counterparty , issuer or borrower performance. It arises any time bank funds are extended , committed , invested or otherwise exposed through actual or implied contractual agreements whether reflected on or off balanced sheet.

Credit Risk segments are:

- i) Default probability , which is the likelihood of non-performance or default of the obligors , including transfer risk
- ii) Concentration and correlation risk which is the risk of credit concentrations due to inadequate diversification of the credit provisions
- iii) Recovery rate risk , which is the loss in case of non - performance or default of the obligors.

The Markets in Turkey international and domestic traders - wholesalers, multinational blue-chip companies, large & medium - small type companies, private lenders activities. The main aim is to benefit from bank's in depth knowledge - has a good reputation individuals in credibility and finance activities and take a large market share in Turkey and international regions.

Turkish banking credit management perceptions is in line with international standards and modern risk management approaches. The risk is perceived as the volatility in earnings and credit risk is perceived as the volatility in the earnings of the bank due to the losses which arise in credit portfolio as a result of the default of the counterparty and difficulty in liquidating the collaterals.

Credit risk assessment is executed in respect of the creditworthiness of the customer, the feasibility of the transaction and the liquidity of the collateral are taken into consideration as a whole granting and utilizing the credit facility. The provisioning and capital allocation for the credit risk is set according to this perception as well in all banks in Turkey.

Turkish bank looks credit risk assessment process depends on the information gathered from both primary and secondary sources of information. Thus gathering accurate information and maintaining it is essential for credit decision process.

On the other hand credit risk qualified in Turkey with via internal risk rating tools, in-house developed credit risk measurement methodology and monitored by a specific MIS system. Credit risk monitoring process includes analyses and reports on transactional ,customer, and portfolio basis. Main goals of the this process are to assess the riskiness, to compare the performance of the portfolio accordance to business strategy, to monitor the exposures according to limits and take the necessary actions accordingly.

5.1.1 Credit Approval Process

The credit process begins with a thorough analysis of the borrower's creditworthiness, or capacity and willingness to repay the loan. The examiner should find an assessment by the credit officer of :

- i) The borrower's current and expected financial condition.
- ii) The borrower's ability to withstand adverse conditions or "stress."
- iii) The borrower's credit history and a positive correlation between historical and projected repayment capacity.
- iv) The optimal loan structure, including loan amortization, covenants, reporting requirements – the underwriting elements.
- v) Collateral pledged by the borrower – amount, quality and liquidity; bank ability to realize the collateral under the worst case scenario. And, Qualitative factors, such as management, the industry and the state of the economy.

The credit granting process starts with the customer acceptance (application - size of limit – credit type – maturity) and end with approval of the credit line(s). Credit department gets involved in this process starting from the review of the credit application package and finalize it approve or reject.

In this process supplementary activities and documentation :

- i) Customer Details (name, establishment,shareholder structure)
- ii) Summary of activities
- iii) Company operations
- iv) Relation with banks (leasing – factoring –trade finance activities)
- v) Collateral
- vi) Proposed Structure
- vii) Financial Analysis

This process begins with the collection, analysis and evaluation of information required to determine the creditworthiness of the borrower seeking credit from the bank. After the credit analysis is completed and borrower has been determined to be an acceptable risk, the credit officer proposes a loan structure for approval that preserves the strengths and protects against identified weaknesses of the borrower. The process ends with determination of a risk rating for the credit and loan approval (or rejection). The bank's credit policy, lending standards and procedures create the parameters for this process, thereby establishing the bank's appetite for risk, conservative or aggressive.

The main goals of preparing credit comments are:

- i) Understanding the operations and structure of the company.
- ii) Providing portfolio wide information on related proposal.
- iii) Providing comments on the collateral structure of the proposal.
- iv) Summarizing findings / discrepancies about credit application forms.
- v) Communicating with front offices in a formal and structured way.
- vi) Understanding structure of proposed transactions.
- vii) Providing summary of the analysis to the credit committee members.
- viii) SWOT Analyses.
- ix) Providing final opinion.

The credit policy and standards should define acceptable loan purposes, types of loans and loan structures, and industries to which the bank is willing to lend, as well as the types of information the lender is required to obtain and analyze. The policy and standards help to create the framework, requirements and tolerance limits for lending in which all bank credit personnel will engage.

5.2. TURKISH BANKS RISK MEASUREMENT SYSTEM & METHODOLOGY

ANALYSIS

In this part I asked comprised of 9 questions to 3 biggest banks and 2 Participation Banks banks in Turkey. Answer adopted the thesis circumstances and result part explain with these answer. (Questions and Tables enclosed to appendix A,)

1) Risk Measurement Framework In Turkey

- i) Types of quantitative credit risk measures system for credit risk influences based on expected loss (EL), unexpected loss (UL) and credit value-at-risk (CVaR) in orderly group by Turkish Bank. Banks generated their risk management especially based on expected loss structure.
- ii) New regulations introduced the concept of a risk group and defined participations as belonging to the same risk group in general TBS (Turkish Banking System Replacing the narrow definition of the risk and previous period so end. Turkish banks generally using risk based pricing / provising/ segmentation / stress test with these concept once.
- iii) Adequate capital must be vied in the context balance sheet structure, within asset quality, earnings por with structure, and systemic environment design. So these result giving us greater profitability and better loan quality can conceivably operate with lor capital ratios within good structure measurement system in the system.

- iv) Participation Banks generally using selected framework with which to comply its control objectives are internationally recognized with requirements set by the Banking Regulation and Supervision Agency of Turkey (BRSA) and considered to be effective at controlling IT-related processes.

2) Early Warning System In Turkish Banking System

- i) In general, the variability of the risk perception of banks show different modellism. Especially rating models and financial analyses using under one group. Some statistical model using with early warning signal. Merton Model and option pricing models rarely using in Turkish banking system
- ii) The portfolio model in the credit risk unit works within the scope of the main tasks defined in relevant regulations in banks group. So TBS manager measure and monitoring of credits taking or proposing measures for the maximization of returns on a portfolio
- iii) Financial Analyses still most important system in banks and particapation banks.

3) Portfolio Risk Measurement Technics In Turkish Banking System

- i) Effectively management style in risk management department there are stil differences between banks. Managing portfolio of loans and used the techniques upper rank techniques unique to banks in process.
- ii) Some banks using their own banking model for rating after than Moddy's KMV / Credits Metrics / Credit Risk + / Credit Portfolio View also using in list
- iii) On the other hand some groups using “Loss giving default + exposy of default + CVAR models”

4) PD - Default Recovery And Default Correlation Mechanism In Turkey

- i) Answer says that all of these system working in correlation.
- ii) On the other hand some banks using; Probability of Default (PD) counterpart will default on its obligation either over the life of the obligation or over some specified horizon. Calculated for a one-year horizon time they are using Expected Default Frequency (EDF) and the variation of the default probability.
- iii) At same time some banks in the event of a default; they are using Exposure At Default (EAD) for the large outstanding obligation

- iv) Loss Given Default (LGD): In the event of a default and its fraction of the exposure recovered through bankruptcy proceedings or some other form of settlement and actual loss compared to the EAD.
- v) Participation banks does not exist these system

5) Tradional and Alternative scoring methods In Turkey

Tradional scoring methods

- i) Multiple discriminant analyses
- ii) Linear probability model
- iii) Logit
- iv) Tobit Model

Alternative scoring methods

- i) CUSUM (Cumulative sum control chart)
- ii) Partial Correction Models

- i) Credit scoring modelling under base tradional scoring methods and alternative scoring methods generally based on multiple discrimanant model in Turkish banks.

For the settle success credit analysts to establish default probabilities for both consumer and corporate loan applicants so these model developed year by year in Turkey. Risk mananagers considering both risk evaulate and design their process in that manner. It is also used to evaluate a set off ratios, or to making analyses more feasibile to bankruptcy.

- ii) Logit using with rating + multiple discriminant +tobit model. These are another section under base in risk management preferences. Risk management manager says that; multiple discriminant analyses has two advantage one of them good performans result for consolidated sector, another is more easier structure for prediction but the biggest dilemma is these method does not exist PD easily.
- iii) Linear probability model generally take more higher result than other method because this method giving more easier paramater for data sourcing and more easier compliance PD result. But some result can be misleading indication for the analyst (estimated data can not be exist ($0 < x < 1$)
- iv) Tobit and Logit model rarely using in scoring model form but some banks using this method with rating + multiple discriminant +tobit variety

Alternative scoring methods;

- v) Cusum is a early warning paramater so it must be include too many datas and time series indicator in model. It's a high level risk management system especially in emerging market “ these model giving good result in regression analysis, stochastic model, multiple correlation and dependent variable concept”. But problem is these model needed long variety datas in sector. Banks fairly using this model in their structure.

6) Using of statistical and software system in the sector

- i) Software
- ii) Statistical model
- iii) Mad/ Lap
- iv) Excel

- i) All sector part using Software model - Statistical model – excel and macro in title (detailed result part)

7) Internal Credit Rating System& Credit Scoring Model System Analyses

- i) The presidency of all Risk except with transactions between Risk Management and the Head of the Business Line. This applies at Group level and Market Risk so its guidelines risk group.
- ii) The main aim there watch that IRS (Internal Rating System) are properly applied inside the Group and that these IRS are effective.
- iii) Validates overrides proposed by analysts on counterparts of its own competence, reviews Quality Control reports about the utilization and performance of IRS
- iv) Monitors the homogeneous application within the Group of the rating and derogation principles for override proposals - quality control division's reports and back-testing results.

8) SA, FIRBA- Advanced Internal Ratings Based Approach AIRBA System

- i) In banking and participation banks sector are standardised approach (SA) using in all bank FIRBA and AIRBA model still in conspectus (still working on main concept)

9) Using Credit Derivatives For Mitigating And Eliminating Models

- i) Turkish Banks generally using Vasicek Model for the manage their derivatives; In practise to measuring risk on a dual risk approach obligors will default on the loan of the risk of loss and recovery of loan principal from the collateral structure and terms of the facility.
- ii) These are quite distinct risks, and proper risk management requires that they be distinctly measured. The obligor risk is the Probability of Default (PD) and the facility risk is the Loss Given Default (LGD).

$$EL = PD * EAD * LGD$$

PD = Probably of Default

EAD = Exposure at Default (Unamortized Balance)

LGD = Loss Given Default (percent)

6. DISCUSSION AND RESULT

To promote new design credit risk modelling and internal control with risk measurement systems, a new practice that requires a well-defined structure and organisation for risk measurement and control has been set with early warning system in banks.

For all banks, credit obligators and international finance giants and their the risk representative is responsible for the identification of the submitted files for which the rating assigned. In this case, the risk representative can ask for the organization of an rating prior to the credit risk level in organization

The specific scales of internal rating systems are the scale of probability of default used for the calculation of the Risk weighted Assets.

For the more effective risk scale must segment group by;

- i) the corporate scale,
- ii) the country scale,
- iii) the bank scale,
- iv) the insurance scale,
- v) the social housing scale,
- vi) the local authorities scale,

Every counterparty receives two internal ratings based on the internal rating systems developed in the framework of the Basel II project: a rating local currency and a rating foreign currency.

The rating local currency has to take into account the domestic economic risk, while the rating foreign currency has to take into account the domestic economic risk and the transfer risk.

For decreasing probability of default risk (Credit risk base in international finance) ;

- i) The probability of default corresponding to the rating assigned to counterparty (on the counterparty scale) is compared with the probability of default related to the country rating (on the country scale) through a mapping to the masterscale
- ii) In case the probability of default of the country is higher than the probability of default of the counterparty, the counterparty rating is said to be constrained by the country rating.

As a result counterparty rating has to be reduced to the rating level (on the counterparty scale) corresponding to the probability of default equal to, or immediately higher than, the probability of default of the multional and counter party risks.

Probability of default related with credit risk. Therefore the main objectives of the credit risk management activities are the systematic specification, monitoring and management of the creditworthiness of counter parties and of the probable risks therein.

For challenges this position re-design risk management by;

- i) Strong, unchallenged and reliable ability and willingness of a foreign parent company located in a better rated country to cover the transfer risk, availability of some form of protection mechanism such as deposit in an offshore reserve account,
- ii) Existence of mechanisms of sovereign “bankruptcy” or moratorium remoteness, access at any time and without limitations to foreign currency and are allod to make overseas payments

- iii) Transactions in which the flows of funds are disconnected from the country of the debtor, existence of important assets in a better rated country, existence of a regular flow of foreign currency revenues from a better rated country,
- iv) Ensure that the hypotheses on which the model is founded are respected; Facilitate the adaptability of the general IRS containment procedure. When functions or anomalies in the use of or results produced by the model are brought to light, swift and effective remedial action must follow.
- v) To this end, control should not only bring to light anomalies but also explains their cause. There must also be a regular and constructive link with the back-testing function, which has the power to modify the model with the approvals.
- vi) To make sure the establishment of IRS containment procedures and the maintenance of the audit trail in the rating process is achieved
- vii) Quality Control's conclusions on each of the tested files will be communicated to the competent Rating Committee quarterly. The tests realized should enable an in-depth analysis of the main override factors.
- viii) The Quality Control Unit must ensure that archives of ratings and their justification are kept updated. On completion of each test, quality control must formalize its controls and justify its conclusions through summaries. The Quality Control function is responsible for adapting the model of these summaries to each IRS and keeping them regularly update.
- ix) The Rating Committee will inform the quality control units of deployment of new version of models and/or new Basel II IRS parameters.

- x) Quality Control must have close ties with the Back-testing and Modeling functions. As the Quality Control unit plays a bigger role than the Back-testing and modeling units, the former's reports must be used as guidance for the audits and tests and the model adjustments undertaken by the latter.
- xi) Moreover, the Quality Control unit is in direct contact with the analysts and tests the correct use of the model, so it is able to consider the comments and any biases observed during use of the IRS and notify them to the Back-testing and Modeling units.
- xii) The importance of the support determines the degree of downgrading or upgrading of the counterpart's rating:
- xiii) A strong or very strong support could upgrade the rating of the counterpart to a level included between its intrinsic rating and those of the support entity. A weak or uncertain support will have no incidence on the rating of the counterpart. A negative support could lead to a downgrading of the rating of the counterparty
- xiv) The control of operational transactions related to the execution of activities, control of communication channels, control of information systems application - control of financial reporting system, control of compliance.
- xv) The utilization data underbase in operational loss are must be collect systematically; accumulated loss data are analyzed and reported to the risk managers.
- xvi) Review process and internal assessment of the amount of capital requirements which guides principles for banks regarding risk control and management processes. This defines principles adequate to their business structure and risk profile in banks historical data for more standart risk approach.

- xvii) Internal use of Basel II compliant Internal Rating Systems (IRS) for capital requirements calculation.
- xviii) The model for internal ratings model; purpose is to assign through the cycle PD ratings on a rating scale equivalent to the Basel II rating scale. To ensure use of a sufficient number of rating classes is used, the masterscale was extended in the range by low or high grades.
- xix) The core of the validation process is localized within two validation departments responsible for Credit Risk Validation and Market Risk Validation respectively.
- xx) For eliminate the international credit risk for unique and coherent across all risks, entities and geographical locations avoiding ineffective and unmanageable discrepancies.
- xxi) Calibration normally denotes the mapping of the Probability of Default (PD) to the rating grades. A rating system is ll calibrated if the estimated PD's deviate only marginally from the actual default rates.

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APPENDIX

APPENDIX 1- QUESTIONS AND ANSWERS

- 1) In banking sector 3 types of quantitative credit risk measures system for measuring credit risk of one asset; expected loss (EL), unexpected loss (UL) and credit value-at-risk (CVaR). How can you using these measurement system in your credit risk management department? Please rank in order of importance for your bank.

Answers:

BANKS	YES	NO	EL	UL	CVAR
A	√		2	3	1
B	√		2	3	1
C	√		2	3	1
Participation Banks	YES	NO	EL	UL	CVAR
X		√			
Y		√			

- 2) In credit risk management early warning models generally adopted in Turkish Banking System. Please rank in order of importance for your bank.

- i) Early warning Signals
- ii) Financial Analyses
- iii) Ratings Model
- iv) Statistical Model
- v) Teoritical Model
- vi) Portfolio Model
- vii) Other (generated in your bank own model)/ Financial Analyses / Ratings Model

Answers:

	ANWERS					
BANKS	Early warning Signals	Financial Analyses	Ratings Model	Statistical Model	Teoritical Model	Portfolio Model
A	3	1	2	4	5	6
B	2	1	3	4	5	6
C	2	1	3	4	6	5
Participation Banks	Early warning Signals	Financial Analyses	Ratings Model	Statistical Model	Teoritical Model	Portfolio Model
X	2	1	3	4	5	6
Y	2	1	3	4	6	5

3) In order to more effectively manage its portfolio of loans and used the techniques listed below please rank in order of importance.

- i) Moody's KMV
- ii) Credits Metrics
- iii) Credit Risk +
- iv) Credit Portfolio View
- v) The Affine Markov Chain Model
- vi) The Black-Scholes-Merton Model
- vii) Credit Migration Matrice Models

Answers:

BANKS	ANSWER						
	Moody's KMV	Credits Metrics	Credit Risk +	Credit Portfolio View	The Affine Markov Chain Model	The Black-Scholes-Merton Model	Credit Migration Matrice Models
A	√		√				
B		√	√				
C		√	√				
Participation Banks	Moody's KMV	Credits Metrics	Credit Risk +	Credit Portfolio View	The Affine Markov Chain Model	The Black-Scholes-Merton Model	Credit Migration Matrice Models
X							
Y							

4) In general in U.S.A and some of European biggest bank using probability of default, recovery rate and default correlation in one risk management system. Are you using these datas in one correlation or how is your mechanism does it work? Please rank in order of importance.

- i) Probability Of Default
- ii) Recovery Rate
- iii) Default Correlation

5) How can you manage your credit scoring modelling under base tradional scoring methods and alternative scoring methods ?

Tradional scoring methods

- i) Multiple discriminant analyses
- ii) Linear probability model
- iii) Logit
- iv) Tobit Model

Alternative scoring methods

- iii) CUSUM (Cumulative sum control chart)
- iv) Partial Correction Models

Answer:

	ANSWER			
BANKS	Multiple discriminant analyses	Linear probability model	Logit	Tobit Model
A	√		√	
B	√		√	√
C	√		√	
Participation Banks	Multiple discriminant analyses	Linear probability model	Logit	Tobit Model
X			√	
Y			√	

- 6) In your bank do you have measurement of credit risk using with portfolio credit risk model /software system?

Answer:

	ANSWER			
BANKS	Software	Statistical model	Mad/ Lap	Excel
A	√	√		√
B	√	√		√
C	√	√		√
Participation Banks	Software	Statistical model	Mad/ Lap	Excel
X	√	√		√
Y	√	√		√

- 7) How does internal credit rating system and credit scoring model working? How is your banking system can correlate this relationship between scoring and internal rating in credit risk management?

Answer :

	ANSWER				
BANKS	Balance Sheet	Modelling Generation	Scoring	Pd	Average
A	√	√	√	√	√
B	√	√	√	√	√
C	√	√	√	√	√
Participation Banks	Balance Sheet	Modelling Generation	Scoring	Pd	Average
X	√	√	√		
Y	√	√	√		

- 8) In Basel 2 there are three types of approaches in credit risk measurement. These are standardised approach (SA), foundation internal ratings based approach (FIRBA) and advanced internal ratings based approach (AIRBA). How do you measure these items?

Answer and Framework:

	ANSWER		
BANKS	(SA)	(FIRBA)	(AIRBA)
A	√		
B	√		
C	√		
Participation Banks	(SA)	(FIRBA)	(AIRBA)
X	√		
Y	√		

- 9) In recent years banks have begun to use credit derivatives for mitigating and eliminating credit risk in their portfolio, how do you managing your credit derivatives in your bank?

CURRICULUM VITAE

Name,Surname: Ahmet AKYILDIZ

Address: B.Düzü / İSTANBUL

Birth Place, Date: Bingöl, 1984

Foreign Language: English,İtalien

Elementary Edu.: Albay Niyazi Esen, 1996

Secondary School: Marmara College, 2003

University: Girne American University, 2008

Graduate School: Bahçeşehir University, 2010

Institute Name: The Graduate School of Social Sciences

Programme Name: Capital Markets and Finance

Business Background : Garanti Bank International NV Credits & Trade Finance - 2011

Finansbank A.Ş. Investment Banking / Project Finance - 2010

Denizleasing AŞ. Credits & Risk Management Division - 2008